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A New Top-Down Approach for Directly Estimating Biomass Burning Emissions and Fuel Consumption Rates and Totals from Geostationary Satellite Fire Radiative Power (FRP)

Authors:

Bernardo Mota^{1,2} and Martin J. Wooster^{1,3, *}

¹ King's College London, Department of Geography, Strand, London WC2R 2LS, UK.

² Present address: European Commission, Joint Research Centre, Ispra, Italy.

³ NERC National Centre for Earth Observation (NCEO), King's College London, Strand, London WC2R 2LS, UK.

*corresponding author (martin.wooster@kcl.ac.uk)

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19 **Abstract**

20 Regional to global-scale biomass burning emissions inventories are primarily based on satellite-
21 derived burned area or fire radiative power (FRP), and most rely on conversions to fuel
22 consumption prior to the emissions estimation stage. This is generally considered the step
23 introducing greatest uncertainty, and some apparently discrete inventories are not fully
24 independent, as they have been cross-calibrated to aid this stage. We present a novel emissions
25 inventory approach that bypasses the fuel consumption step, directly linking geostationary FRP
26 measures to emission rates of total particulate matter (TPM), via coefficients derived from
27 observations of smoke plume aerosol optical depth (AOD). The approach is fully ‘top-down’,
28 being based on spaceborne observations alone, is performed at or close to the FRP data’s original
29 pixel resolution, and avoids the need to assume or model fuel consumption per unit area prior to
30 the emissions calculation. Rates and totals of trace gas and carbon emission can be inferred from
31 the TPM fluxes, and in combination with satellite burned area (BA) products the approach provides
32 an innovative top down approach to mapping fuel consumption per unit area (kg.m^{-2}) as a last step
33 in the calculation. Using this innovative methodology, which we term ‘FRE_{emissions}’ (FREM), we
34 generate a 2004 – 2012 fire emissions inventory for southern Africa, based on Meteosat FRP-
35 PIXEL data. We find basic annual average TPM emissions 45% higher than the widely used
36 GFASv1.2 inventory, with our higher totals in line with independent assessments that necessitate
37 a significant upscaling of GFAS TPM emissions to match observed AODs. Our estimates are also
38 12% higher than GFEDv4.1s, which already includes a substantial upward adjustment for fires too
39 small to be detected by the MODIS MCD64A1 BA product. If we adjust the FREM-derived
40 emissions for SEVIRI’s inability to detect the lower FRP component of the regions fire regime
41 then the differences between FREM and GFAS / GFED grow further, to a mean of 64% with
42 respect to GFED4.1s TPM emissions for example. These upwardly adjusted FREM estimates

43 agree very well with FEER, an FRP- and AOD-based inventory driven by polar-orbiting MODIS
44 FRP ‘snapshots’ rather than geostationary observations. Similarly higher totals are seen for
45 FREM’s fire-emitted trace gases, derived using the emission factor ratios of gases to particulates.
46 Our exploitation of geostationary FRP requires fewer assumptions than use of polar orbiter FRP
47 measures, avoids biases coming from incomplete sampling of the fire diurnal cycle, and enables
48 the FREM approach to provide fire emissions and fuel consumption estimates at a higher spatio-
49 temporal resolution than any inventory currently available (e.g. 0.05°, and hourly averages or
50 better), including per km² of area burned. The approach offers great potential to generate very high
51 resolution fire emissions datasets for the tropics, sub-tropics and potentially temperate zones, with
52 updates available in near real-time from the global suite of geostationary meteorological satellites
53 operated by organisations such as EUMETSAT (Meteosat), NOAA (GOES) and JMA (Himawari).
54

55 1. INTRODUCTION

56 Accurate inventories of landscape fire emissions are required to assess influences on regional and
57 global atmospheric composition, weather and climate (Andreae and Merlet, 2001; Akagi *et al.*,
58 2011). Biomass burning is amongst the greatest source of atmospheric fine particulate matter
59 (PM_{2.5} and PM₁₀; Reddington *et al.*, 2016), resulting in significant impacts on human health (Pope
60 *et al.* 2002). For certain air pollutants like carbon monoxide (CO), landscape fires are among the
61 most dominant source (Andreae and Merlet, 2001), whilst for others (e.g. hydrogen cyanide; HCN)
62 seemingly the only major source (Li *et al.*, 2000). Every landscape fire emits CO₂ as its main
63 product (Andreae and Merlet, 2001; Wooster *et al.*, 2011), even those dominated by smouldering
64 combustion (e.g. Huijnen *et al.*, 2016), and fires in tropical forests and peatlands contribute very
65 significantly to the net growth of atmospheric CO₂ (van der Werf *et al.*, 2009; Huijnen *et al.*, 2016).

66
67 Landscape fire emissions show large variabilities across all timescales (e.g. Roberts and Wooster,
68 2008; Roberts *et al.*, 2009; van der Werf *et al.*, 2011; Kaiser *et al.*, 2012; Andela *et al.*, 2016), and
69 only satellite Earth Observation (EO) can drive large-scale, regularly updated emissions
70 inventories. Thus far, no inventory delivers both relatively fine (e.g. ~ hourly or better) spatial and
71 temporal (e.g. ~ 5 km or better) resolution, nor full agreement with independent atmospheric
72 observations (e.g. see comparisons by Shi *et al.*, 2015; Pereira *et al.*, 2016; Reddington *et al.*,
73 2016). Differences stem from (i) limitations in the EO data and algorithms used for fire
74 identification and characterisation (e.g. Boschetti *et al.*, 2004; Freeborn *et al.*, 2009; Randerson *et al.*,
75 2012; Nogueira *et al.*, 2016), (ii) difficulties in estimating fuel consumption per unit area
76 (kg.m²) and total fuel consumption (kg) for the identified fires (e.g. Reid *et al.*, 2009; Roberts *et al.*,
77 2011; Kaiser *et al.*, 2012), and (iii) uncertainties involved in estimating emissions of
78 particulates and gases from fuel consumption totals (e.g. Vermote *et al.*, 2009; Van Leeuwen *et al.*

79 *al.*, 2011). Whilst EO data and algorithms for use in (i) have improved substantially based on polar
 80 orbiting MODIS and VIIRS (e.g. Boschetti *et al.*, 2004; Giglio *et al.*, 2013; 2016; Schroeder *et al.*,
 81 2014), and second generation geostationary systems such as Meteosat SEVIRI (e.g. Wooster *et*
 82 *al.*, 2005; 2015), and more detailed emissions factor databases have become available for use in
 83 (iii) (e.g. Akagi *et al.*, 2011; Huijnen *et al.*, 2016), there has been relatively less progress in (ii)
 84 with regards to converting satellite fire radiative power (MW) or burned area (m²) measures into
 85 fuel consumption estimates (Andela *et al.*, 2016). This remains an area of key uncertainty (Reid *et*
 86 *al.*, 2009), and for this reason we focus here on a new fire emissions methodology that bypasses
 87 the fuel consumption estimation step and directly relates fire emissions to FRP observations, the
 88 latter available at very high temporal resolution from geostationary orbit. This innovative approach
 89 significantly limits the number of assumptions required in the emissions calculation, particularly
 90 compared to burned area based methods, and reduces sources of uncertainty involved in the ‘fuel
 91 consumption estimation’ stage that pose difficulties even when combining burned area and FRP
 92 data together (e.g. Roberts *et al.*, 2011; Andela *et al.*, 2016). Our approach builds on research with
 93 polar orbiting satellite FRP and AOD data started by Ichoku and Kaufman (2005), but by using
 94 the near continuous geostationary FRP observations we limit the assumptions required. We term
 95 this new methodology ‘FRE_{emissions}’ (FREM), since use of temporally-integrated geostationary
 96 FRE data are key. Fuel consumption (kg), including on a per unit area basis (kg.m⁻²), can be
 97 estimated as a last step if required, based on either the inverse of the TPM emissions factor or the
 98 calculated total carbon in the emissions released.

100 **2. LANDSCAPE FIRES AND EMISSIONS INVENTORY METHODOLOGIES**

101 Landscape fires occur in most vegetated ecosystems. Most herbaceous biomes typically show finer
 102 fuels and more flaming combustion, along with lower fuel consumptions per unit area [kg.m⁻²] and

the strongest dominance of CO₂ in their smoke (Akagi *et al.*, 2011; Wooster *et al.*, 2011; van Leeuwen *et al.*, 2014). Fires in more wooded areas, along with those burning organic soils such as peat, typically show higher fuel consumptions per unit area, a tendency towards more smouldering combustion, and higher proportions of CO and total particulate matter (TPM) in their smoke (e.g. Andreae and Merlet, 2001; Huijnen *et al.*, 2016). All current emissions inventories use emission factors [EF_x, g.kg⁻¹] to specify how much of chemical species *x* is released per kg of fuel consumed. The biome-dependent summary EFs of Andreae and Merlet (2001) and its updates (e.g. as reported in Kaiser *et al.*, 2012), and/or those in Akagi *et al.* (2011), are used in most cases. Therefore, the primary reason independent fire emissions inventories show not only spatial and temporal discrepancies, but also differences in magnitude, comes not from the deployed EFs but from the differing estimates of total fuel consumption (e.g. Roberts *et al.*, 2011; Larkin *et al.*, 2014; Knorr *et al.*, 2012; Kaiser *et al.*, 2012). This is in part because fuel consumptions per unit area vary markedly, even within the same biome (e.g. Reid *et al.*, 2009; Kukavskaya *et al.*, 2012; Sommers *et al.*, 2014; van Leeuwen *et al.*, 2014; Weise and Wright, 2014; Andela *et al.*, 2016), and this variability is difficult to track precisely.

118

119 **2.1 Burned Area Based Methodologies**

Most ‘bottom up’ approaches to fire emissions estimation are currently driven by burned area (BA) measures [m²], mostly derived from daily 500 m spatial resolution MODIS data (e.g. Giglio *et al.*, 2013). This highly successful approach delivers high quality BA mapping across many biomes, though smaller burns can remain undetected and lead to significant fire emissions underestimation in ‘small-fire’ dominated ecosystems (Randerson *et al.*, 2012; Zhang *et al.*, 2017). To estimate total fuel consumption, the BA data must be combined with fuel consumption per unit area [kg.m⁻²] estimates, themselves calculated from somewhat uncertain fuel load [FL; kg.m⁻²] and

‘combustion completeness’ [C; unitless] metrics (Reid *et al.*, 2009; Vermote *et al.*, 2009; van Leeuwen *et al.*, 2014). Successful emissions inventories such as the widely used Global Fire Emissions Database (GFED; van der Werf *et al.*, 2010) use this bottom-up formulation to deliver spatially explicit fuel consumption totals to which biome specific EFs are then applied, and GFED currently delivers monthly emissions estimates (0.25° grid cells) around a year after the MODIS MCD64A1 BA data become available. To account for unmapped ‘small fire’ BA, the most recent GFED v4.1s also applies a BA ‘boost’ based on active fire detections (Van der Werf *et al.*, 2017), though the methodology (based on Randerson *et al.*, 2012) remains to be fully validated.

135

136 **2.2 FRP Based Methodologies**

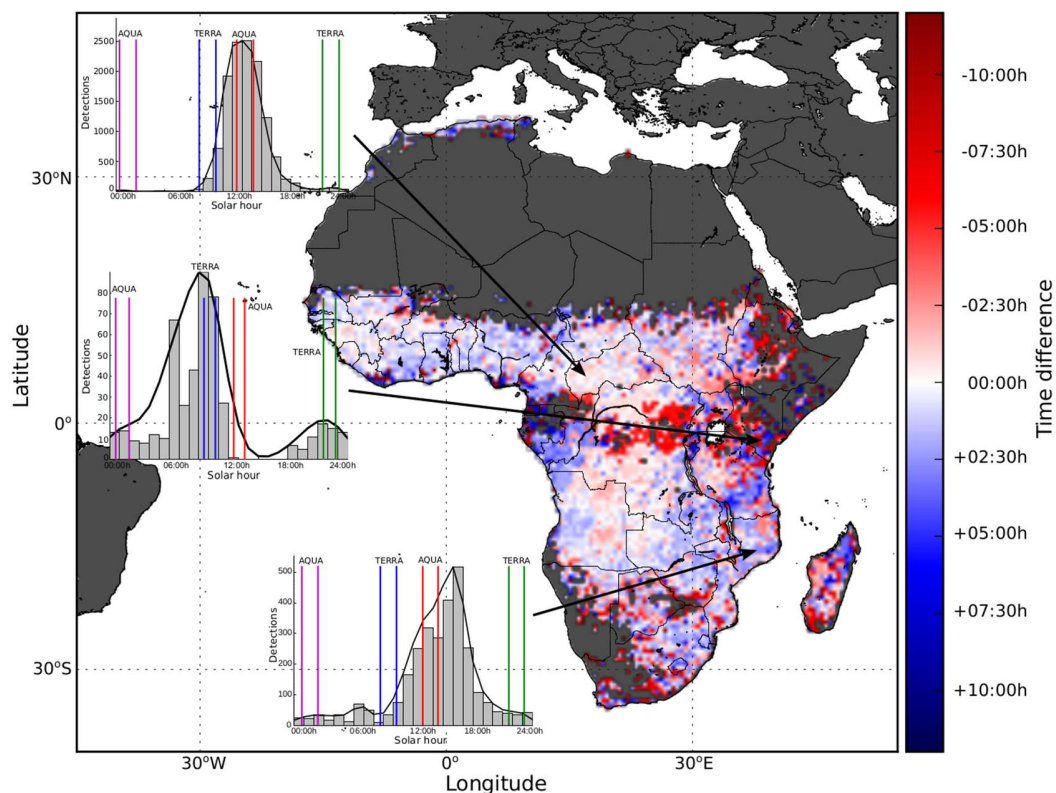
137 An alternative to BA-based fire emissions inventory methods are FRP-based approaches, where
138 FRP observations integrated over a fire’s lifetime are used to estimate fire radiative energy (FRE)
139 release. Since even fires covering 10^{-3} to 10^{-4} of a pixels area can be detected from polar or
140 geostationary orbit, even rather small fires can be included in this integration (Roberts *et al.*, 2005).
141 However, some fires will remain below the sensors minimum FRP detection limit (Roberts *et al.*,
142 2015). Furthermore, whilst small-scale experiments show FRE is directly relatable to total fuel
143 consumption with minimal dependence on vegetation type (Wooster *et al.* 2002; 2005; Kremens
144 *et al.*, 2012), the linear scalar between FRE and biomass burned may show a biome dependence
145 when observing FRP from orbit, in part because different proportions of the fire-emitted FRP
146 maybe missed across different biomes (e.g. because of variable tree canopy cover; Freeborn *et al.*,
147 2009). Nevertheless, FRP approaches can in theory (i) remove reliance on the more difficult-to-
148 estimate fuel load and combustion completeness metrics required by ‘bottom up’ methods, (ii)
149 enable impacts of far smaller fires to be incorporated than when using burned area measures alone
150 (Wooster *et al.*, 2005; Kaiser *et al.*, 2012), and (iii) provide much quicker information delivery, at

151 higher temporal resolutions, than BA-based methods (e.g. Kaiser *et al.*, 2012; Hertwig *et al.*, 2013;
152 Roberts *et al.*, 2015; Huijnen *et al.*, 2016). However, the simple and consistent conversion between
153 FRP and fuel consumption rate found in the laboratory (e.g. Wooster *et al.*, 2005) may not hold
154 between biomes when using satellite FRP measures, and if only polar orbiting FRP ‘snapshots’
155 are used then most burning occurs when fires are not being observed by the sensor.

156

157 The most widely used FRP-based emissions inventory is delivered by the Global Fire Assimilation
158 System (GFAS: Kaiser *et al.*, 2012), operated as part of the Copernicus Atmosphere Monitoring
159 Service (CAMS: <https://atmosphere.copernicus.eu/>). GFAS uses the FRP approach to map mean
160 fuel consumption globally (daily, 0.1°) from weighted averages of MODIS’ FRP ‘snapshots’.
161 GFAS’ conversion between FRP and fuel consumption is based on biome-specific conversion
162 factors [β , kg.MJ⁻¹] derived from comparisons between GFAS’ monthly FRP totals and the
163 matching GFED v3.1 dry matter fuel consumptions (Kaiser *et al.*, 2012). This is a pragmatic and
164 sensible solution to converting satellite-derived FRP data into fuel consumption estimates, but has
165 the disadvantage of building back into the FRP-based approach uncertainties inherent in GFEDs
166 pre-fire fuel load and combustion completeness parameters (Reid *et al.*, 2009; Vermote *et al.*,
167 2009), as well as any biome-dependent biases in the MODIS BA product (e.g. Giglio *et al.*, 2013).
168 It also means that GFAS and GFED are driven to provide rather similar fuel consumption totals
169 and thus fire emissions, limiting their independence (Kaiser *et al.*, 2012). More independent FRP-
170 based methodologies are provided by the Fire Energetic and Emissions Research (FEER) system
171 (Ichoku and Ellison, 2014), the Brazilian Biomass Burning Emission Model with FRP assimilation
172 (3BEM_FRP) (Pereira *et al.*, 2016) and IS4FIRES (Soares *et al.*, 2015), which all relate MODIS
173 FRP measures directly to fire emissions without recourse to a fuel consumption estimation stage.
174 Our new FREM methodology builds on this type of formulation - extending it to exploit the

175 advantages of geostationary FRP observations in order to avoid the many spatio-temporal
176 sampling issues inherent in use of polar-orbiting FRP data alone (which can lead to FRE under- or
177 over-estimation (Roberts *et al.*, 2009; Freeborn *et al.*, 2011; Wiedinmyer *et al.*, 2011; Kaiser *et al.*,
178 2012; Andela *et al.*, 2015). Use of multi-day MODIS FRP data can reduce such sampling biases,
179 but creates only low temporal resolution FRE estimates (Vermote *et al.*, 2009; Freeborn *et al.*,
180 2011). Combining FRP snapshots with diurnal cycle parameterisations may provide higher
181 frequency estimates, assuming the early afternoon MODIS overpass roughly captures the daily fire
182 activity peak (e.g. Ellicott *et al.*, 2009; Vermote *et al.*, 2009; Freeborn *et al.*, 2011; Andela *et al.*
183 2015), but as demonstrated in Fig. 1 the time difference between the maxima of the fire diurnal
184 cycle and the afternoon MODIS overpass shows significant spatial variation, as does the fraction
185 of the total daily fire pixel count that occurs during the MODIS overpass window (Fig. 2). Where
186 the latter is particularly low, daily FRE (or average FRP) measures derived from MODIS are more
187 prone to bias, potentially leading to spatially varying differences between such FRE totals and
188 actual fuel consumptions. This is likely to be a key driver of the need for GFAS' biome-dependent
189 conversion factors [β] that link daily MODIS-derived FRE and fuel consumption (Kaiser *et al.*,
190 2012), with additional factors including biome dependent biases in the MCD64A1 BA data that
191 drive GFED, to which GFAS is calibrated (Giglio *et al.*, 2013).



192

193

194 **Figure 1.** Mapped difference (hrs) between the time of maximum active fire pixel count (i.e. daily
 195 fire activity peak) and the ± 1 hr window encompassing the MODIS local solar overpass time
 196 (which depends on changing location within the MODIS swath). Data are for 2010 and based on
 197 Meteosat Second Generation (MSG) SEVIRI FRP-PIXEL Product available from the
 198 EUMETSAT LSA SAF (Wooster *et al.*, 2015), spatially aggregated into 0.5° grid cells. Subset
 199 graphs show example histograms of FRP-PIXEL active fire detections for three 0.5° grid cells
 200 located over eastern Central African Republic, Northern Mozambique, and southern Kenya, with
 201 a functional fit to these data and the four MODIS overpass windows per day also indicated. Only
 202 fire detections with confidences $> 50\%$ are included (Wooster *et al.*, 2015).

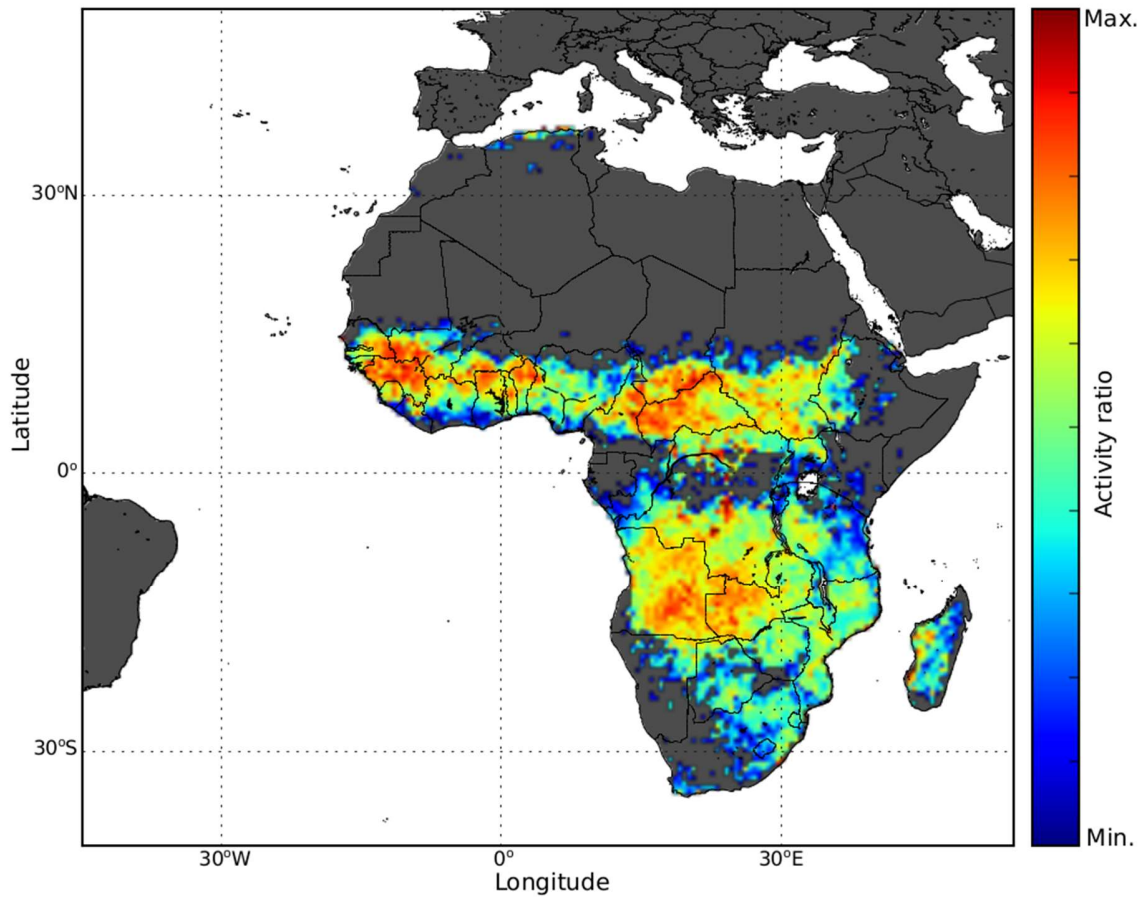


Figure 2. Spatial distribution of active fire detection opportunities offered by the MODIS sampling windows shown in Fig. 1. This is expressed as the ratio of the Meteosat SEVIRI FRP-PIXEL active fire detections made within the ± 1 hr window surrounding the four daily MODIS overpass times (shown in Fig. 1) to the total number of daily detections. Source data are those of Fig. 1.

Further factors challenging the use of spatially-invariant FRE to fuel consumption conversion factors, is that spaceborne FRP data are subject to geographically-varying measurement artefacts absent from laboratory-scale observations. These include (i) blocking of a proportion of surface

214 fire FRP by any overlying tree canopy (e.g. Freeborn *et al.*, 2014; Mathews *et al.*, 2016), (ii) FRE-
215 biases caused by the presence of different proportions of active fire pixels below the sensors FRP
216 detection limit (e.g. Schroeder *et al.*, 2008; Freeborn *et al.*, 2009; Roberts *et al.*, 2015), and (iii)
217 varying flame depths and soot volume fractions leading to varying flame emissivity's (Johnson *et*
218 *al.*, 2015). The magnitude of such artefacts depends on the ecosystems vegetation and/or fire
219 regime (Edwards, 1984; Chuvieco *et al.*, 2008), furthering the biome dependence of satellite-
220 derived FRP (or FRE) to fuel consumption relations.

221

222 3. DETAIL ON THE FRE_{EMISSIONS} APPROACH TO FIRE EMISSIONS ESTIMATION

223 FREM is designed to deal with a series of limitations that currently impact use of the satellite fire
224 radiative power approach by;

225

226 (i) Removing observation biases that stem from the incomplete sampling of the fire diurnal
227 cycle provided by polar-orbiters. FREM uses geostationary FRP observations, and in
228 addition to removing the type of biases shown in Fig. 1, further benefits of such near-
229 continuous FRP data in relation to smoke emissions transport modelling have been
230 demonstrated by e.g. Baldassarre *et al.* (2015) and Roberts *et al.*, (2015).

231 (ii) Deriving relations that link FRP to fire emissions fluxes and fuel consumption rates
232 that inherently account for gross, inter-biome variations in FRP measurement bias.
233 Such biases include, the changing wavelength-dependent emissivity of flames that will
234 vary between fire types dominating the different biomes (Johnson *et al.*, 2015), and the
235 changing degree of tree-canopy interception of surface fire FRP, highlighted as an issue
236 by Freeborn *et al.* (2014) and demonstrated by Mathews *et al.* (2016).

(iii) Removing the need to link satellite FRP observations to fuel consumption rates using factors derived in small scale experiments that may not be fully representative when using satellite-FRP measures of landscape scale fires (e.g. Wooster *et al.*, 2005), or which are based on landscape-scale fuel consumption metrics stemming from burned-area based emissions inventories such as GFED. Use of the latter by e.g. Kaiser *et al.* (2012) removes the independence of the FRP-based emissions calculations and builds into the methodology issues affecting BA based inventories, such as current inability to detect many ‘small area’ and/or sub-canopy fires (Randerson *et al.* 2012) and uncertainties in the fuel load per unit area and ‘combustion completeness’ terms (Reid *et al.*, 2009).

FREM estimates emissions of total particulate matter (TPM) directly from geostationary FRP data via application of biome-dependent ‘smoke emissions coefficients’ [C_{biome}], these being calculated from per-fire matchups of FRE and smoke plume aerosol optical depth (AOD). Freeborn *et al.* (2008) and Ichoku *et al.* (2008) already demonstrated strong relations between FRP and aerosol flux in the laboratory, and applying this approach to satellite derived FRP data removes many of the assumptions and interdependences discussed in Section 2. Trace gas fluxes can be subsequently estimated from the TPM emissions via application of the appropriate emissions factor ratios.

The FEER approach of Ichoku and Ellison (2014) already uses biome-dependent TPM ‘smoke’ emissions coefficients [C_{biome} , [kg.MW⁻¹]] to deliver a ‘top down’ emissions methodology fully independent of fuel consumption-based methods. FEERs coefficients were derived from combinations of instantaneous MODIS FRP (MW or J.s⁻¹) and TPM emission rate (F_e , [kg.s⁻¹])

261 data, the latter calculated from simultaneously timed MODIS AOD products combined with plume
262 height and wind-speed estimates. Smoke plume heights are often rather uncertain (e.g. Sofiev *et*
263 *al.*, 2012; Paugam *et al.*, 2016), and a single FRP measure may not reflect the time-integrated FRP
264 characteristics a fire typically shows over the hours needed to generate the type of large-scale
265 plume observable in the 10 km MODIS AOD data (Baldassarre *et al.*, 2015; Roberts *et al.*, 2015).
266 Indeed, bias seems likely because some of the smoke present in these large plumes will have been
267 generated earlier in the diurnal cycle than the MODIS FRP observation made simultaneously with
268 the AOD assessment. To help counteract this, Ichoku and Ellison (2014) match only part of the
269 plume to the instantaneous FRP measure, which required assumptions on wind speed and direction
270 at plume height. A key advantage of FREM's use of semi-continuous geostationary FRP data is
271 that it allows each matchup to be based on the fire's entire FRP time-series, and its entire smoke
272 plume AOD recorded at the moment of the MODIS overpass, removing the sampling-time bias,
273 reliance on smoke plume height and velocity, and the need to select only a fraction of each fire's
274 plume.

275

276 4. SMOKE EMISSION COEFFICIENTS DERIVATION

277

278 4.1 Geographic Area and Biome Delineation

279 This first FREM implementation focuses on southern hemisphere Africa (0.0 - 34.0° S, 8.0 - 52°
280 E), a region showing a prolonged annual dry season (July to Sept) during which herbaceous
281 vegetation is either dry or dormant and deciduous leaves contribute to the preponderance of fire
282 (Archibald *et al.*, 2009). The regions wetter areas often sustain closed-canopy forests with
283 prolonged moist conditions and heterogeneous vegetation structures that can constrain fire spread,
284 whilst drier grasslands and more open forests and woodland savannas tend to host larger and more

285 spatially contiguous fires, albeit with reduced accessibility to higher fuel loads. We used the
286 GLOBCOVER 2009 landcover map (validated by Bicheron *et al.*, 2011), derived from 300 m
287 spatial resolution ENVISAT MERIS observations, to derive our biome classification. Unlike the
288 single ‘savanna’ class used by GFED and GFAS, we map grassland and woodland savanna biomes
289 separately, as recommended by the Intergovernmental Panel on Climate Change (IPCC, 1997)
290 guidelines for GHG emissions reporting (Korotzi *et al.*, 2004). Our aggregated landcover classes
291 are functions of the four main GLOBCOVER vegetation structure groups of Managed Lands
292 (including Croplands), Shrubs & Herbaceous, Grasslands, and Trees & Woody (Sophie *et al.*,
293 2010), and we subdivided the latter into Closed Forest and Open Forest/Woodlands (also
294 sometimes termed woodland savanna). The resulting final five biomes we term closed forest,
295 managed lands, shrublands, and two types of savanna - Open Forest/Woodland (woodland
296 savanna), and Grasslands/Savanna (grassland savanna). The spatial distribution of these five
297 biomes (shown in Fig. 3) is in fact very similar to the independently-derived Southern African
298 woodland-grassland classification of Korotzi *et al.* (2004), derived by thresholding the MODIS
299 percentage tree cover product (Hansen *et al.*, 2002). We derived C_{biome} coefficients for our five
300 biomes via per-fire matchups of FRE and AOD-estimated plume mass of total particulate matter
301 [TPM; kg].

302

303 4.2 Fire Radiative Power and AOD Datasets

304 Geostationary FRP data came from the EUMETSAT Land Surface Analysis Satellite Applications
305 Facility (LSA SAF: <http://landsaf.meteo.pt>) Meteosat SEVIRI FRP-PIXEL product (15-min, 3 km
306 resolution at the sub-satellite point), fully described in Wooster *et al.* (2015). Comparison to
307 simultaneous MODIS FRP data indicates low bias on a per-fire basis, though the lowest FRP fires

(FRP \leq 40 MW) are typically under-counted by SEVIRI compared to MODIS due to the formers larger nadir pixel area (Roberts *et al.*, 2015).

310

Similar to Ichoku and Ellison (2014), we used MODIS 550 nm 10 km spatial resolution AOD data (Collection 6 MOD/MYD04_L2; Levy *et al.*, 2013) to derive plume TPM. AOD's from Terra MODIS (~ 10:30 am) and Aqua (~ 1:30 pm) are generated using two retrieval algorithms, Dark Target - developed to work over dense dark vegetation, and Deep Blue - developed originally to provide coverage over brighter surfaces but now expanded to all cloud-free land. A combined AOD data layer, based on a merge algorithm, is also provided to minimise coverage gaps. FREM uses the Deep Blue output because it only needs coverage around the selected matchup fires and because these shows best agreement with southern Africa AERONET AODs (Sayer *et al.* 2014).

319

4.3 Fire Matchup Selection

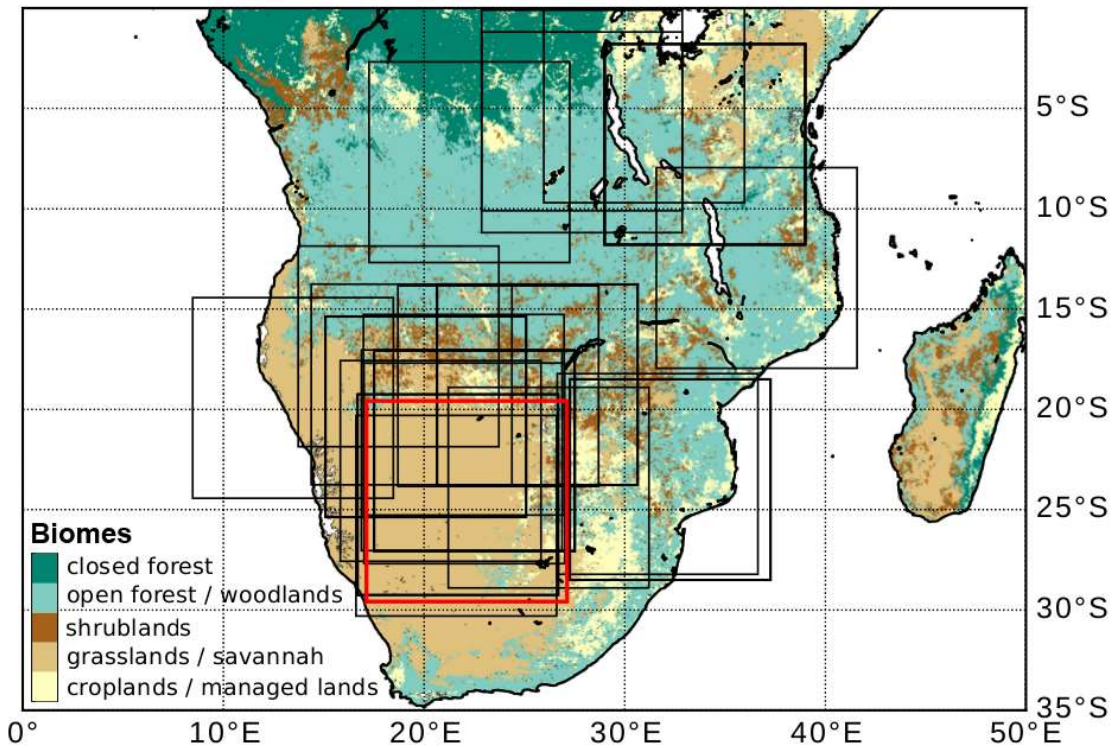
To aid matchup selection, cloud-cover information from the LSA SAF Meteosat SEVIRI FRP-PIXEL Quality Product were used (Wooster *et al.*, 2015), along with 10 m height mean zonal wind fields from ERA interim reanalyses (Balsamo *et al.*, 2015). Cloud and wind velocity screening masks were applied to daily composites of SEVIRI FRP accumulated up to the local MODIS overpass time. Simple criteria were used to identify regions containing potential matchup fires:

326

- (i) Cloud free conditions, to provide the FRP record of an entire fire.
- (ii) Near surface winds $\geq 5 \text{ ms}^{-1}$, to aid generation of substantial smoke plumes.
- (iii) A high total sum of SEVIRI-derived FRP ($\geq 1000 \text{ MW}$) up to the time of the MODIS overpass, to ensure the presence of many potential matchup fires.

331

332 To help identify sufficiently isolated matchup fires, a series of morphological operations were also
 333 applied to the daily screened composites. These combined criteria allowed us to select a series of
 334 500 km × 500 km target regions (Fig. 3), within which matchups were identified.



335
 336
 337 **Figure 3.** FREM biome map of southern Africa, based on reclassification of the GLOBCOVER
 338 2009 landcover map and appearing similar to the woodland/grassland classification of southern
 339 Africa derived by Korontzi *et al.* (2004). Outlines show the thirty-one 500 km × 500 km target
 340 regions from which matchup fires used to generate the biome-dependent FREM smoke emissions
 341 coefficients (C_{biome}) of Fig. 7 were selected. Red outlined region has its FRP time-series shown in
 342 Fig. 4.
 343 Each of the target regions outlined in Fig. 3 were examined across a ten-day period around the date
 344 of the identified fire activity highlighted using tests (i) to (iii) and the morphological operations

described above. The FRP time-series of each region was used to identify the time of day at which fire activity was minimal, and this was used as the start time for each FRP temporal integration period to calculate the per-fire FRE, with the end time being the that of the respective Terra and Aqua MODIS AOD product used in the matchup (Fig. 4). The need to find fires whose plumes were spatially isolated from others did limit the search area/times somewhat – as some regions and periods that matched most of our criteria showed so much smoke it was difficult to isolate individual plumes. Future work will endeavour to improve on this by exploiting far higher spatial resolution AOD products, rather than the 10 km data used herein.

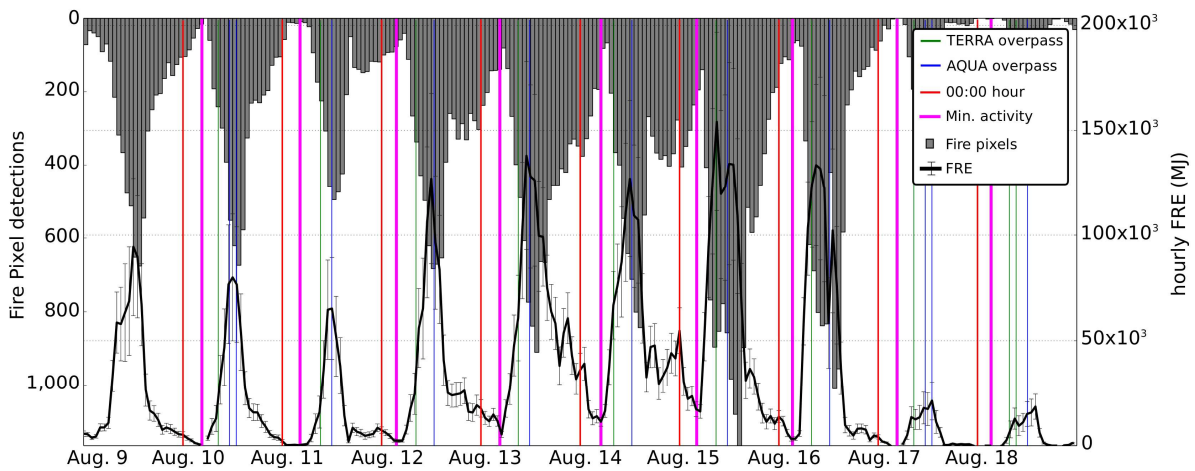
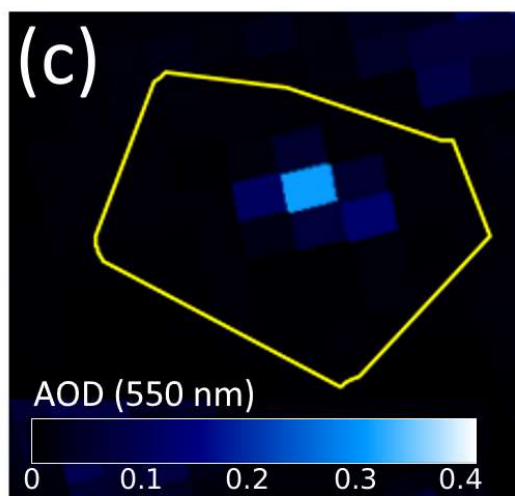
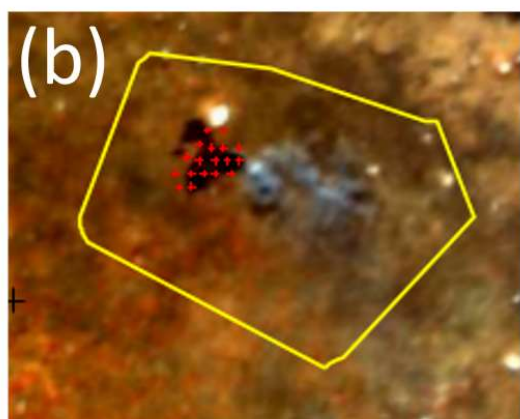
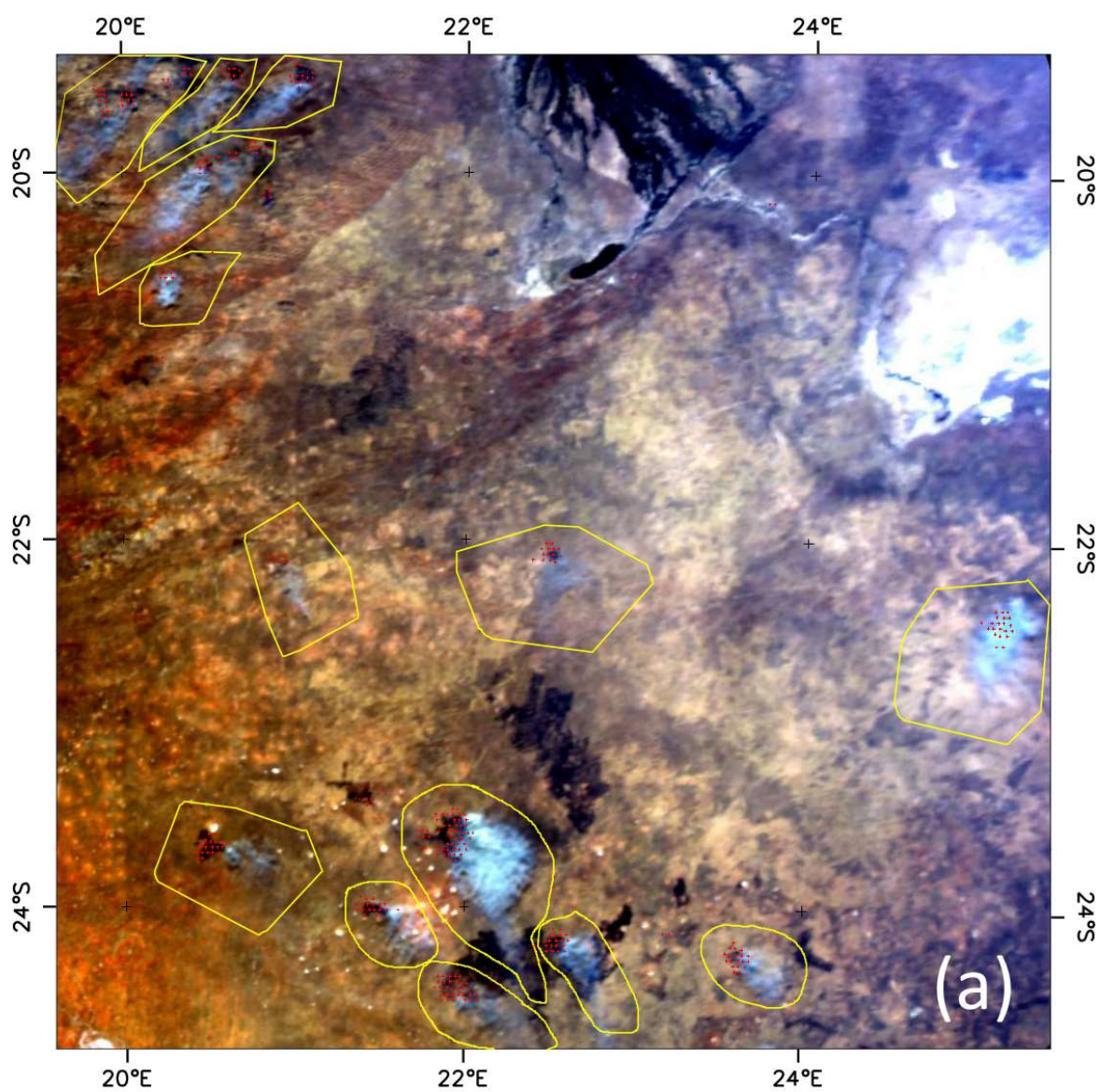


Figure 4. Time series of SEVIRI hourly active fire pixel detections (grey bins) and hourly FRE (black line) for the 500 km × 500 km region highlighted in red in Fig.3 in August 2011, located south of the Okavango Delta (see imagery in Fig. 5). Overpass times of Terra and Aqua MODIS are shown by green and blue vertical lines respectively, alongside daily solar noon (red) and the daily time of minimum fire activity minimum (magenta). Error bars on hourly FRE are calculated

362 from the FRP uncertainties delivered in the geostationary FRP-PIXEL product (Wooster *et al.*,
363 2015).

364

365 Each of the thirty-one regions, identified between July 2011 and November 2011, shown in Fig.
366 3, contained many candidate matchup fires, each composed of multiple active fire pixels (Fig. 5a,
367 b). Only those for which a single GLOBCOVER class represented more than 50% of the active
368 fire pixel locations were retained, in order to avoid burns that showed too much consumption of
369 mixed biome vegetation. This still left hundreds of candidate fires (Fig. 5a), and for each the smoke
370 plume was outlined and the corresponding AOD data examined (Fig. 5b, c). Fires were removed
371 where incorrect masking of smoke as cloud had clearly occurred in the AOD products, or where
372 non-biomass burning aerosols or surface reflectance effects seemed likely to have erroneously
373 contributed to AOD, for example at the Etosha Pan (Namibia) or Kalahari (Botswana).



375 **Figure 5.** Example region of southern Africa from which matchup fires were selected on the
 376 afternoon of 12th Aug 2011, 12:40 UTC (MODIS Aqua overpass). (a) Region outlined in red in
 377 Fig. 3, south of the Okavango delta, depicted as a colour composite using data from the Aqua
 378 MODIS afternoon overpass [RGB=1(0.6 μ m), 4(0.55 μ m), 3(0.47 μ m)]. Smoke plumes from
 379 candidate active fires are outlined with yellow vectors, and the centre locations of each SEVIRI
 380 active fire pixel detected from the time of the identified active fire minimum (shown in Fig. 4) up
 381 until this Aqua overpass time are shown as red dots. (b) Zoom around the bottom left fire and
 382 plume shown in (a) to indicate detail. The dark burn scar left by the fire can clearly be seen. (c)
 383 Matching MYD04_L2 AOD data derived from the Aqua MODIS overpass shown in (b).

384

385 Each retained matchup fire had its FRE and column-integrated mass of emitted total particulate
 386 matter (TPM) estimated. The former from the temporal integration of FRP over the fire's lifetime,
 387 and the latter from the summed excess AOD ($\sum \Delta \text{AOD}$) of the outlined smoke plume, with any
 388 pixel partly or wholly encompassed by the vector included in the AOD summation (Fig. 5c and
 389 Fig. 6). All plumes were large enough to be covered by more than one 10 km AOD pixel, most by
 390 many pixels, as seen from the examples in Fig. 5 and 6. The column-integrated mass of emitted
 391 TPM was calculated following Ichoku and Ellison (2014) as the surplus 550 nm AOD above the
 392 (non-plume) AOD background (which varied over time due to e.g. smoke from prior or distant
 393 fires), multiplied by the ratio of the AOD product pixel area (m^2) to the light extinction efficiency
 394 per unit of biomass burning aerosol mass ($\beta_e, \text{m}^2.\text{g}^{-1}$). $\beta_e(550 \text{ nm})$ was selected as $3.5 \pm 1.0 \text{ m}^2.\text{g}^{-1}$,
 395 based on values listed in Table 1 for 'fresh' smoke taken from studies conducted primarily within
 396 southern Africa (plus other savanna-type fires). Ichoku and Kaufman (2005) and Ichoku and
 397 Ellison (2014) assumed a higher β_e of $4.6 \text{ m}^2.\text{g}^{-1}$, at the top end of our range, which was selected
 398 as a 'global average' applicable to plumes across all fire-affected global environments. A

399 substantially higher $7.6 \pm 1.9 \text{ m}^2.\text{g}^{-1}$ value was assumed by Vermote et al (2005) (based on Chin
400 *et al.* 2002), again for global aerosols and in that case not only from ‘fresh’ smoke. Abel *et al.*
401 (2005) indicate β_e typically increases as smoke ages.

402

403 **Table 1.** Values of light extinction efficiency per unit of biomass burning aerosol mass (β_e , $\text{m}^2.\text{g}^{-1}$)
404 ¹), also termed the smoke mass extinction coefficient, appropriate for 550 nm unless otherwise
405 stated. A mean β_e of $3.5 \pm 1.0 \text{ m}^2.\text{g}^{-1}$ was used herein, based on these studies.

406

$\beta_e (\text{m}^2.\text{g}^{-1})$	Reference	Notes
2.22 (3.37)	Abel <i>et al.</i> (2005)	Fresh southern African biomass burning smoke (and value for ‘aged’ regional ‘haze)
3.8 – 4.5	Reid <i>et al.</i> (2005a)	Smoke from Zambian savanna burning
4.5	Andrews <i>et al.</i> (1989)	Computed mass extinction coefficient of ‘dry’ smoke.
4.14 ± 1.06	Weinman et al (1981)	Savanna fires (Australia), assessed at 500 nm and assumed ~ 10% lower for 550 nm.

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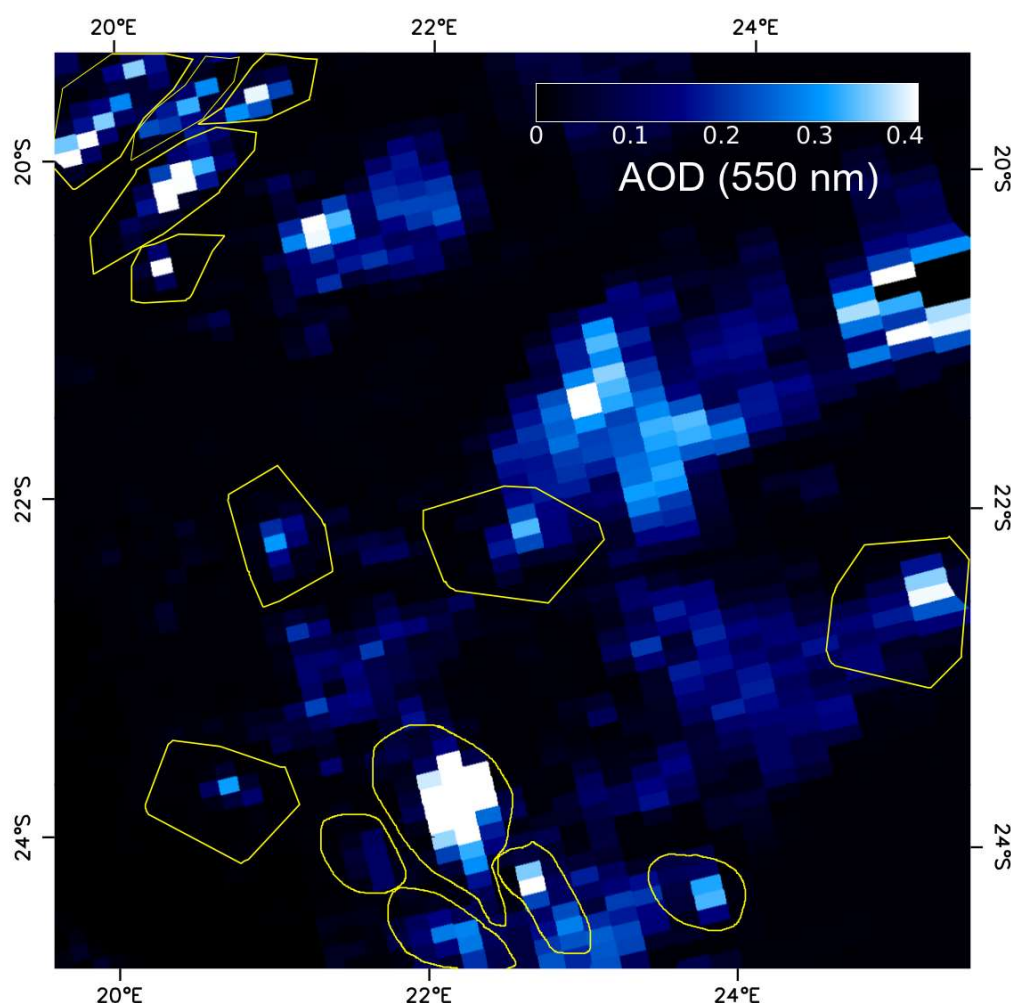


Figure 6. MODIS Aerosol optical depth (AOD) data matching the MODIS image shown in Fig. 5a. The yellow outlines from Fig. 5 here encompass the set of $10 \text{ km} \times 10 \text{ km}$ MODIS AOD product pixels that are included in the plume-integrated AOD calculation for each fire. Any pixel partly or wholly encompassed by the vector is included in the AOD summation, which is then used to estimate the mass of total particulate matter in the plume. Some areas of apparently high AOD are unrelated to biomass burning and so are not outlined here, for example that immediately south of the Okavango Delta (*cf.* Fig. 5) neighbouring a highly reflective salt pan.

4.5 Derivation and Interpretation of Smoke Emissions Coefficients (C_{biome})

Final smoke emission coefficients for each biome are shown in Fig. 7 and were derived from the per-fire FRE and plume TPM matchups using linear orthogonal distance regression, which takes into account uncertainties in both datasets (Reed, 1989). Derived C_{biome} values range from $13.03 \pm 0.23 \text{ g.MJ}^{-1}$ (Grasslands) to $65.63 \pm 0.91 \text{ g.MJ}^{-1}$ (Closed Canopy Forest). Our SEVIRI-derived $C_{grassland}$ value is very similar to the laboratory derived $14.4 \pm 4.3 \text{ g.MJ}^{-1}$ determined by Freeborn *et al.*, (2008) using IR camera-derived FRP and filter-based aerosol measures, and lies towards the middle of the $10 - 19 \text{ g.MJ}^{-1}$ range found for laboratory burns of southern African grasses (Ichoku *et al.*, 2008). Our value for Open Canopy Forests/Woodlands ($19.75 \pm 0.49 \text{ g.MJ}^{-1}$) is also similar to the $18 \pm 5 \text{ g.MJ}^{-1}$ calculated by Ichoku and Ellison (2014) for southern African savannas (Zambia), using MODIS FRP data and the FEER methodology, though our SEVIRI-derived value has significantly lower uncertainty – perhaps reflecting our more discrete land-cover classification that distinguishes Grassland Savanna from Open Forest/Woodland Savanna (Fig. 3).

Ichoku and Ellison (2014) found the MODIS-derived C_{biome} for southern African forests (D.R. Congo; $15 \pm 6 \text{ g.MJ}^{-1}$) to be lower than that of Grassland, which is perhaps surprising since FRP observations in forests would be expected to be more affected by canopy interception of the upwelling fire-emitted thermal radiation, and forest burns also typically show greater particulate matter emissions per kg of fuel burned than do grassland burns (Akagi *et al.*, 2011). The smoke emissions coefficients for Closed Canopy Forest and Open Canopy Forest/Woodland Savanna we derive using SEVIRI and the FREM methodology (Fig. 7a, b) are, respectively, $\times 5$ and $\times 1.5$ what we find in Grassland Savanna (Fig. 7d), and we find this potentially more appropriate than values lower than for Grassland Savanna. We suggest similarly that tree canopy interception of upwelling surface-fire emitted FRP is likely also responsible for at least part of the higher FRE-to-fuel consumption ‘conversion factor’ derived for tropical forest biomes compared to savanna biomes

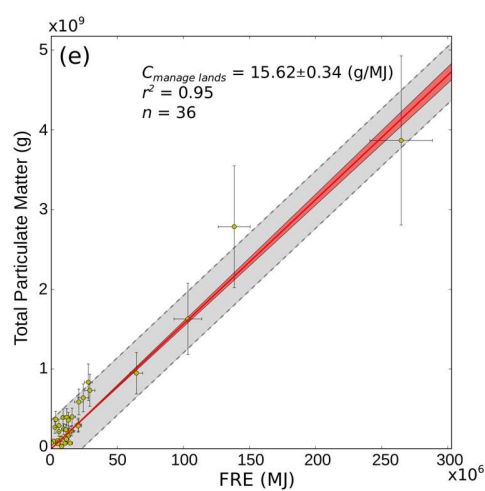
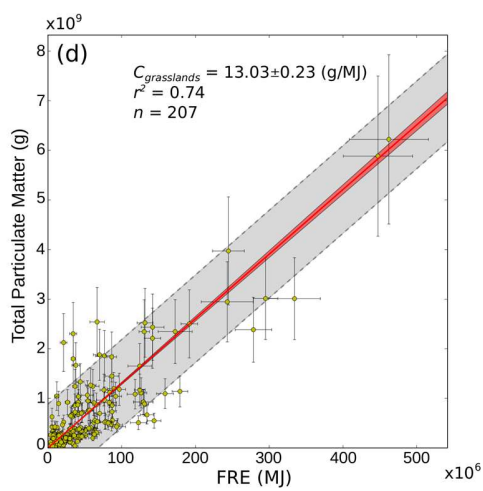
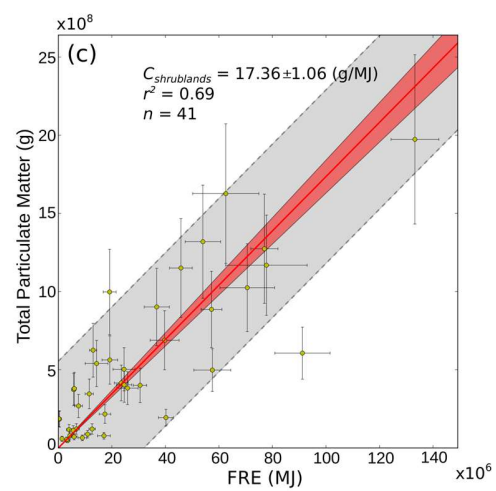
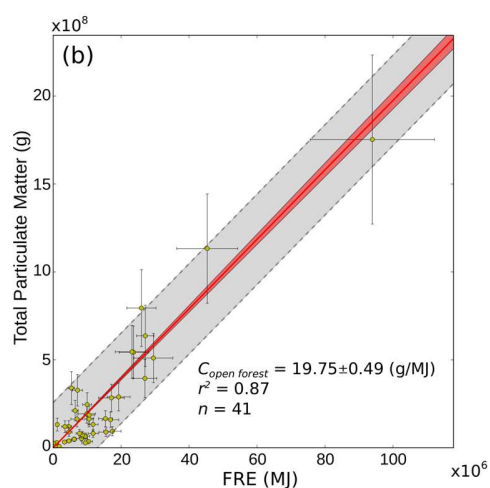
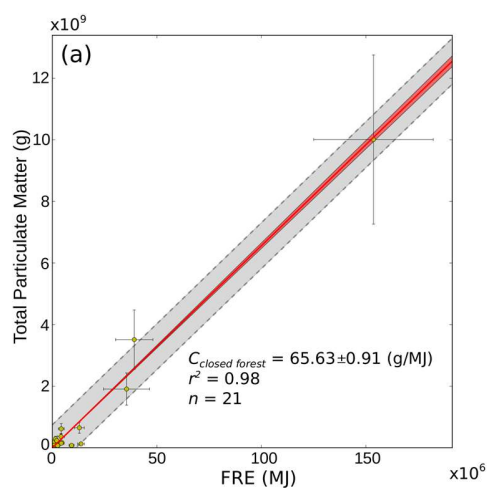
443 during the calibration of GFAS v1.2 with GFED v3.1 (Kaiser *et al.*, 2012). Biome-dependent
444 differences in the performance of GFED, for example in relation to burned area detectability
445 (which can vary significantly between savannas, tropical forests and agricultural burning areas for
446 example; Giglio *et al.*, 2010; Randerson *et al.*, 2012), may also play a part. By relating FRE directly
447 to particulate matter release using emissions coefficients derived from the satellite observations
448 themselves, FREM bypasses some of the issues affecting other fire emissions inventories, enabling
449 it to be both fully independent of GFED and GFAS and to consider the observational
450 characteristics of the satellite FRP measures of each biome (e.g. increasing amounts of canopy
451 interception of upwelling fire emitted thermal radiation in biomes with a higher mean percentage
452 tree cover).

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463 **Figure 7.** Biome dependent smoke emissions coefficients (C_{biome} , g.MJ⁻¹) derived from the slope
464 of the linear best fit made between the amount of total particulate matter in a plume (grams) and
465 the amount of radiative energy released by the causal fire (FRE, MJ). Red shaded area represents
466 the 95% confidence interval on this slope (i.e. the uncertainty in C_{biome}), whilst the grey shaded
467 area represents the prediction interval (i.e. the interval encompassing to 95% probability the value
468 of TPM given a single value of FRE). Coefficients are shown for the biomes of (a) Closed Canopy
469 Forest, (b) Open Canopy Forest and Woodland (Woodland Savanna), (c) Shrublands, (d)
470 Grasslands (Grassland Savanna), and (e) Managed lands (including Croplands). For each biome,
471 each data point represents a single fires FRE calculated from a series of Meteosat FRP-PIXEL
472 products (Fig. 4), and specifically from the fire activity minimum up until the time of the satellite
473 overpass from which the matching smoke plume TPM was estimated from the MODIS AOD
474 product (Fig. 5; Fig. 6). Uncertainties in FRE (1σ) are derived from the FRP-PIXEL uncertainty
475 metrics (Wooster *et al.*, 2015), whereas those in TPM are derived from the $\pm 1.0 \text{ m}^2.\text{g}^{-1}$ uncertainty
476 in the assumed smoke aerosol extinction cross-section (Table 1) and the MODIS AOD uncertainty
477 layer. MODIS AOD uncertainties estimates correspond to one-standard-deviation Gaussian
478 confidence interval of the envelopes resulting from the comparison of retrieved AOD data and
479 AERONET measures. These depend on the AOD, QA flag, and viewing geometry (Sayer *et al.*,
480 2013).

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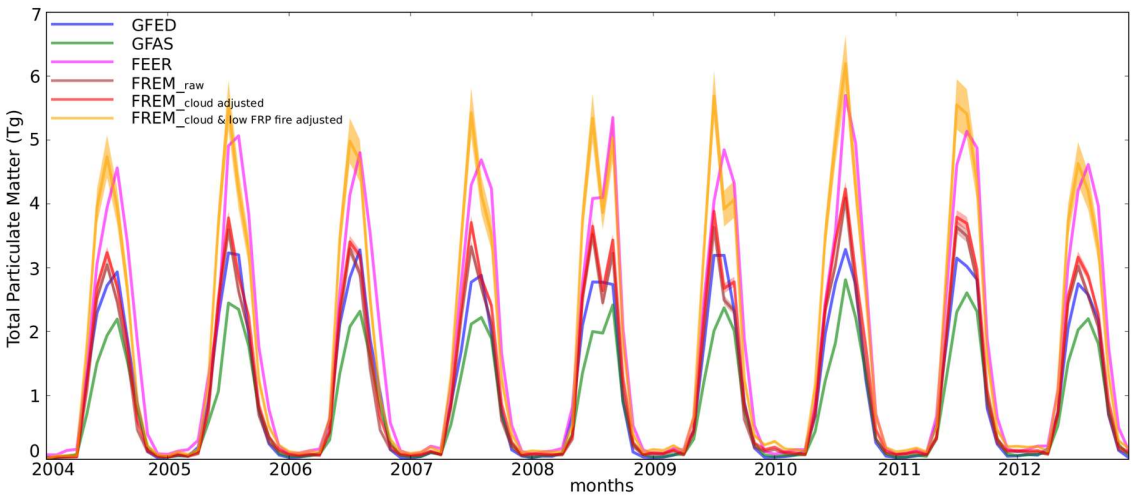
483 5. APPLICATION TO EMISSIONS INVENTORY DEVELOPMENT

484

5.1 Emissions of Total Particulate Matter (TPM)

The smoke emissions coefficients derived in Section 4 were applied to hourly averages of the Meteosat SEVIRI FRP-PIXEL products described in Wooster *et al.* (2015), thus calculating pixel-based TPM emissions rates (g.hr^{-1}). To account for the fact that each SEVIRI pixel can contain more than one biome – especially in fragmented areas and transition zones - the fractional coverage of each of our five biomes was calculated for each pixel, and the relevant area weighted average smoke emissions coefficient used. Coefficients were in fact applied to three versions of the FRP-PIXEL data - (i) the basic FRP observations made at the native SEVIRI spatial resolution, (ii) those adjusted by the cloud cover fraction (δ) stored in the matching FRP-GRID product (5° resolution), and (iii) those adjusted by cloud-cover fraction and an additional factor accounting for under-counted ‘small’ (i.e. low FRP) fires at or below the nominal SEVIRI FRP minimum detection limit. Each FRP dataset is fully detailed in Wooster *et al.* (2015). Fig. 8 shows the resulting monthly FREM-derived time-series of TPM emissions, alongside those of GFEDv4.1s (Van der Werf *et al.*, 2017; www.globalfiredata.org/), GFASv1.2 (Kaiser *et al.*, 2012; www.gmes-atmosphere.eu/about/project_structure/input_data/d_fire/) and FEERv1.0-G1.2 (Ichoku and Ellison, 2014; www.feer.gsfc.nasa.gov/data/emissions/). Differences between FREM monthly ‘raw’ and ‘cloud adjusted’ TPM emissions are typically low and within the uncertainty of the ‘raw’ estimates alone throughout most fire seasons (except late season 2009), indicating that most fires in southern Africa typically burn far away from significant cloud cover. FREM’s mean cloud adjusted TPM emissions are $(1.96 \pm 0.39) \times 10^7 \text{ Tg.year}^{-1}$, 45% higher than GFAS v1.2 and 12% higher than GFED v4.1s (which already includes a substantial upward adjustment for fires whose burned area is too small to be detected by MODIS; Van der Werf *et al.*, 2017), but lower than those of FEER by a margin of $\sim 30\%$.

509 The TPM emissions distribution between the different biomes is shown in Table 2, and for the
 510 peak fire months of July/August, mean FREM cloud-adjusted TPM emissions are 50% higher than
 511 GFAS, 27% lower than those of FEER, and 12% higher than GFED v4.1s. The GFED burned
 512 area and/or fuel consumptions per unit area would overall therefore need to be increased by
 513 relatively minor amounts for the resulting emissions to match those of FREM – though when
 514 FREM emissions are adjusted for the low FRP component of the regions fire regime - which is
 515 undetectable by SEVIRI but detectable by MODIS (shown by e.g. Freeborn *et al.*, 2009) – FREM’s
 516 mean annual TPM emissions increase more substantially above GFED v4.1s (to an average of
 517 64%), with an even higher difference when compared to GFAS v1.2 (Fig. 8). These cloud-adjusted
 518 FREM emissions of total particulate matter are, however, within 1% of those provided by the
 519 MODIS FRP-based FEER inventory.



520
 521 **Figure 8.** Monthly total particulate emissions estimates for southern African fires, derived from
 522 the FRE_{emissions} methodology (FREM) applied to the SEVIRI FRP-PIXEL product of Wooster *et*
 523 *al.* (2015) for 2004-2012. Three versions are shown, those based on ‘raw’ SEVIRI FRP
 524 observations, those adjusted for cloud cover, and those adjusted for ‘cloud cover and under-
 525 detected low FRP fires’ (see Section 5.1 and 5.2). The associated uncertainties are shown in each
 526 case. Corresponding TPM emissions from the GFED v4.1s, GFAS v1.2 and FEER v1.0 inventories

527 are shown for comparison, and the cloud and low FRP fire adjusted FREM values calculated from
528 SEVIRI lie very close to the MODIS-derived FEER estimates.

529

530

531 **Table 2.** Emissions of total particulate matter (TPM; Tg) per year across southern Africa, as
532 calculated using the FREM approach (Cloud and low FRP adjusted version), along with the
533 percentage contributed by the different biome types of Fig. 3.

534

		% of TMP Emissions in a Biome				
	Annual TPM Emissions (Tg)	Closed Forest	Shrublands	Croplands / Managed Lands	Open Forest / Woodland Savanna	Grassland Savanna

200						
4	14.7	23.4	14.0	11.3	45.3	5.9
200						
5	16.1	25.3	13.9	12.0	42.6	6.3
200						
6	14.4	25.5	13.1	11.5	43.5	6.3
200						
7	16.2	24.0	14.0	12.2	42.0	7.8
200						
8	17.4	25.6	13.4	12.4	40.4	8.2
200						
9	16.1	25.4	13.3	11.5	42.8	6.9
201						
0	19.3	25.1	13.2	12.5	39.5	9.8
201						
1	17.3	22.6	14.1	11.8	38.0	13.5
201						
2	15.6	25.0	13.8	11.5	39.9	9.9

535

536

537 5.2 Low FRP Fire Adjustment

538 As seen in Fig. 8, the ‘low FRP fire’ adjustment (Wooster *et al.*, 2015) increases FREM’s TPM
539 emissions substantially compared to the ‘cloud-adjusted’ values alone. Freeborn *et al.* (2009;
540 2014) describe in detail the bias adjustments needed to be made to SEVIRI’s FRP data when

541 deriving total FRP or FRE metrics, which are required to account for low FRP fire pixels below
542 the SEVIRI minimum FRP detection limit. At the scales used here, a simple 46% upscaling
543 delivers a SEVIRI-derived FRP dataset with very low bias ($\sim 2\%$) compared to simultaneous
544 MODIS FRP observations (Roberts *et al.*, 2015), and this adjustment is included here. However,
545 with the FREM approach it is possible that the adjustment should be of a smaller magnitude. This
546 is because, whilst the generally high FRE fires used for the smoke emissions coefficient derivation
547 (Fig. 7) have their FRP very well measured by SEVIRI at the time of the afternoon MODIS
548 overpass, with only a 3 MW mean bias seen in southern Africa (Roberts *et al.*, 2015), earlier in
549 their lifetime these fires will likely have included areas burning below SEVIRI's minimum FRP
550 detection limit but whose smoke will have contributed to the AOD of the matching plume. Thus
551 the resulting smoke emissions coefficient will already likely account for some of the impact of fire
552 pixels burning below the SEVIRI sensors minimum FRP detection limit, though the extent of this
553 is unknown at present. For now therefore, the 46% upward adjustment used in the FRP-GRID
554 product (Wooster *et al.*, 2015; Roberts *et al.*, 2015) is also applied in FREM as the 'low FRP fire'
555 adjustment

556

557 **5.3 TPM Emissions Interpretation**

558 Outputs from FREM (cloud- and low-FRP fire adjusted) agree very well with those of FEER, are
559 very significantly higher than those of GFAS (factor of $\times 2.2$), and are also higher than GFED
560 (against which GFAS is calibrated) (Fig. 8). The implication that GFAS may significantly
561 underestimate of TPM emissions across southern Africa agrees with Kaiser *et al.* (2012), who
562 found GFAS's southern African aerosol emissions required a $\times 3$ upward scaling to replicate AOD
563 observations. Those of GFEDv3.1 (whose carbon emissions for southern Africa are around 20%
564 lower than GFEDv4.1s used here) are reported to require a $\times 2$ upscaling (Tosca *et al.*, 2013), and

565 Reddington *et al.* (2016) report need for similar upscalings based on an alternative aerosol model.
 566 FREM cloud- and low-FRP fire adjusted emissions therefore appear more consistent with TPM
 567 emissions totals stated to reproduce satellite AOD's in southern Africa than are those of GFAS
 568 and GFED.
 569
 570 In addition to differences in magnitude, Fig. 8 also indicates timing differences between emissions
 571 inventories. Across the nine years, FREM shows maximum TPM emissions in July - except for
 572 August in 2010 - and GFED an almost even split between these two months. FEER shows peaks
 573 in August (apart from 2008 in Sept), as does GFAS (apart from 2008 again in Sept, and in 2005
 574 July). To help explore the reasons, Fig. 9 depicts for 2012 the percentage of daily FRE measured
 575 by SEVIRI that is released (a) during the two-hour window surrounding the four daily MODIS
 576 overpasses, and (b) by fires in each of the five biomes. Daily FRE (grey line) is high throughout
 577 most of June to August, and the proportion of daily FRE released around the MODIS overpass
 578 time also remains reasonably constant (Fig. 9a), with both starting to decrease more significantly
 579 from mid-September onwards. The July and August differences in month of maximum TPM
 580 emissions between FREM (which uses geostationary FRP) and FEER and GFAS (which both use
 581 MODIS FRP) seem therefore not to be due to a significantly changing fire diurnal cycle with
 582 respect to MODIS' sampling times. Fig. 9b indicates however that a significant shift in the biomes
 583 being most affected by fire occurs between July and August, with an increase in the proportion of
 584 total FRE released in Grassland Savannas with respect to Open Forest/Woodland Savannas. In
 585 FREM, the smoke emissions coefficient for Grasslands is significantly lower than that of the higher
 586 fuel load Open Forest/Woodlands (Fig. 7), which is identifiable only because our biome classes
 587 discriminate between these two savanna types as recommended by IPCC (1997). Other fire
 588 emissions inventories predominantly classify these as a single biome, and so are largely invariant

589 to the distinction. FREM’s more discrete biome mapping appears to be the primary reason that it
590 reports TPM emissions decreasing from July to August, because more of the fires are burning in
591 grassland savanna biomes dominated by finer fuels whose emissions contain, on average, less
592 particulate matter per unit of fuel consumed compared to more wooded savanna areas. Going into
593 September, a diurnal cycle change does appear to occur, as the percentage of total radiative energy
594 released during the MODIS overpass times decreases more markedly than during the two prior
595 months (Fig. 9a), and the proportion of fires in grasslands and managed lands increases (Fig. 9b).
596

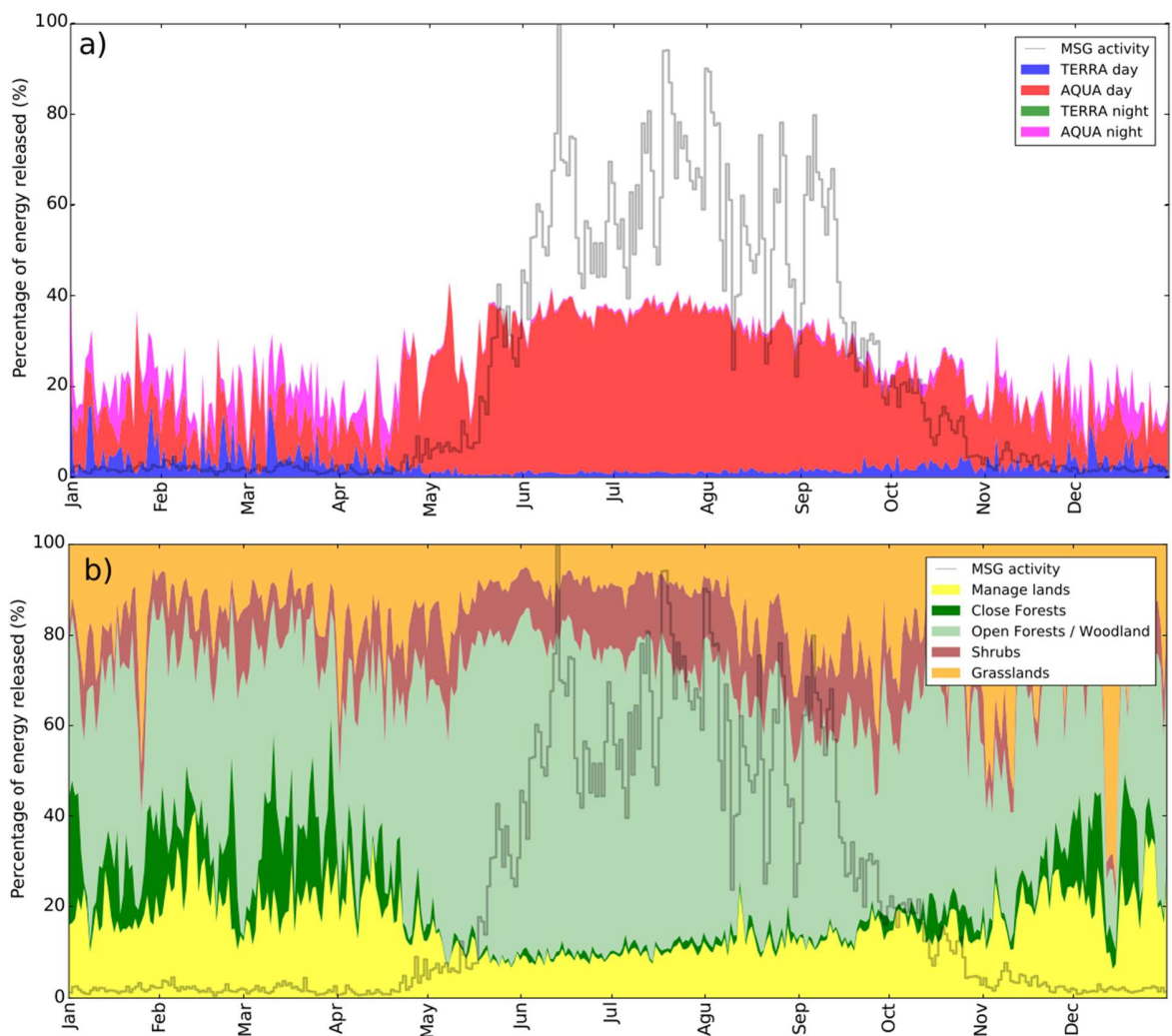
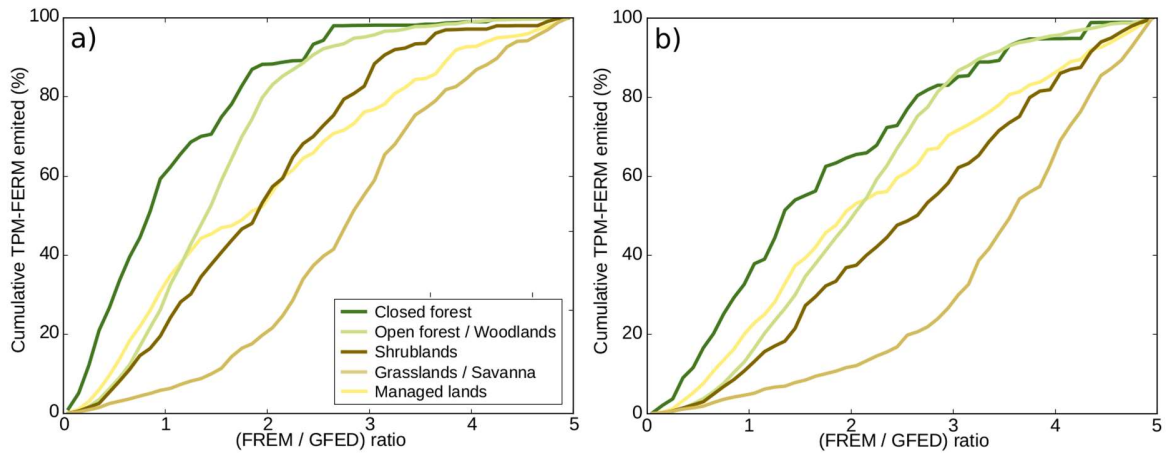


Figure 9. Percentage of daily FRE calculated from the Meteosat SEVIRI FRP-PIXEL product for 2012 that is released (a) during the ± 1 hr window encompassing the MODIS overpass time, and (b) in each biome. For comparison to the percentage values, fire activity expressed as daily FRE from MSG SEVIRI is also shown (grey line, scaled from 0 to 100%).

5.4 Comparison to GFEDv4.1s

To explore in more detail per-biome TPM emission differences between FREM and GFED4.1s, Figure 10 shows the cumulative sum of FREM's emissions as a function of the ratio of those of FREM to GFED4.1s (calculated for GFEDs 0.25° grid cells and for both cloud adjusted FREM (Fig. 10a) and cloud and low FRP fire adjusted FREM (Fig. 10b)). Discounting adjustment of the TPM emissions factor, this ratio describes the change required to the GFEDv4.1s burned area and/or fuel consumption per unit area measure of a grid cell such that the cells TPM emissions would equal those of FREM. Taking the Open Forest/Woodland Savanna biome first (which is responsible for over half of the overall TPM emissions; Fig. 9b), Figure 10a shows that in the cloud-corrected FREM inventory, 26% of emissions are accounted for by grid cells where FREM's emissions are lower than GFEDv4.1s (i.e. FREM-to-GFED TPM ratio < 1.0), with a further 33% having a ratio in the range 1.0 to 1.5. For these cells, GFED burned area \times fuel consumption per unit area metric would need to decrease or increase by a maximum of 50% for their emissions total to equal that of FREM (noting that GFED will have classed some of the cells as different biomes compared to FREM, and using only a single savannah class). Open Forest/Woodland Savanna cells needing more than a doubling of GFED4.1s burned area \times fuel consumption per unit area are responsible for only a small fraction ($\sim 10\%$) of the biomes FREM emissions. The equivalent figures for other biomes can be extracted from Fig. 10a, and in order of their overall TPM emissions totals, the biomes of Open Forest/Woodland Savanna, Grassland Savanna, Managed

622 Lands and Shrublands show FREM TPM emission estimates 1.1, 2.3, 1.2, and 1.4× higher than
 623 GFED4.1s respectively, whereas Closed Forests are lower (0.7×). Overall, FREM’s cloud-adjusted
 624 TPM emissions are 12% higher than GFED4.1s, but adjustment for low FRP fires increases the
 625 above ratios by a factor of 1.46 and substantially increases overall FREM TPM emissions above
 626 GFED4.1s (see Section 5.1), resulting in a consequent increase in the per-grid cell ratios as well
 627 (Fig. 10b).

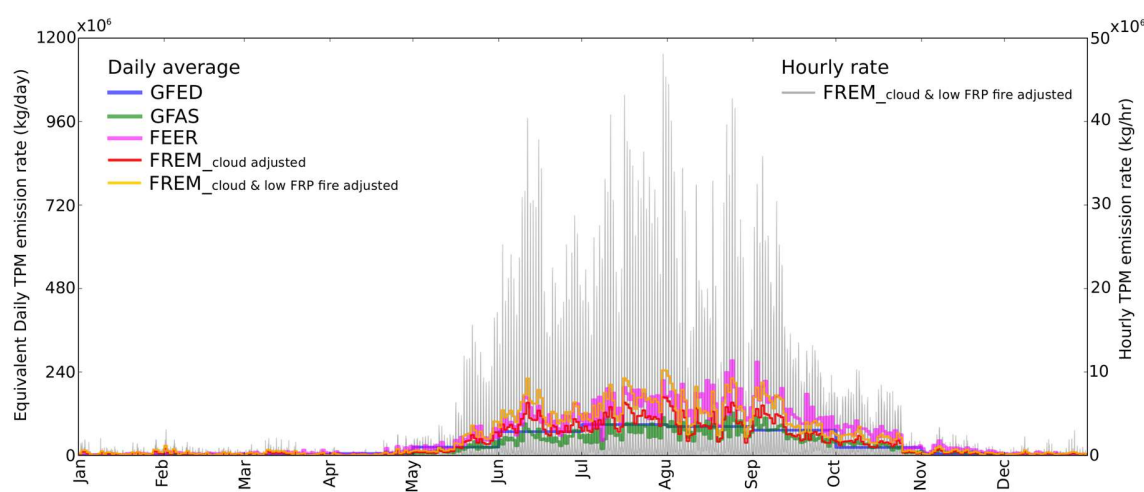


633 **Figure 10.** Cumulative sum of FREM-derived TPM emissions (%), expressed as function of the
 634 per-grid cell FREM-to-GFED v4.1s emissions ratio. Calculations were performed using the 0.25°
 635 grid cells of GFED, and 85% of cells had non-zero values in both inventories. < 1% of cells had a
 636 non-zero Colours are the same as those mapped in Fig. 3. (a) shows the results using the cloud-
 637 corrected FREM, and (b) the cloud and low FRP fire corrected FREM.

639 5.4 High Spatio-Temporal Resolution Emissions Estimates

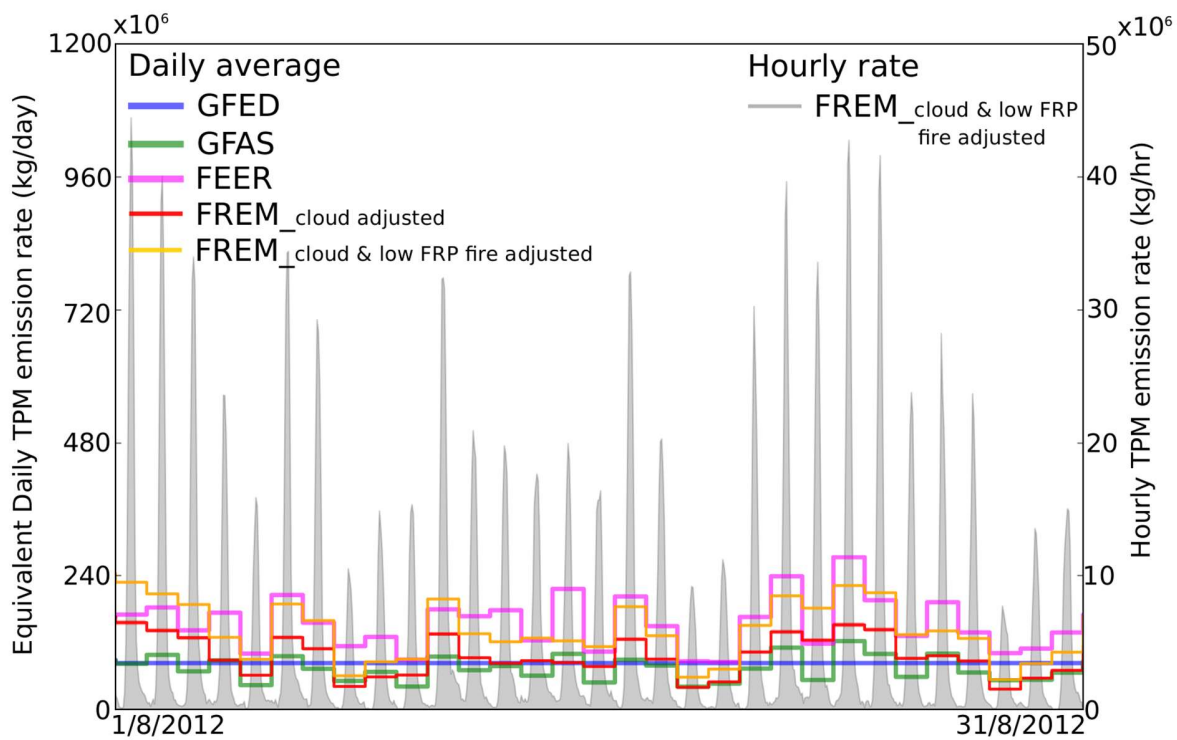
640 Fig. 11 shows FREM's hourly TPM emission rate [$\text{kg}\cdot\text{hr}^{-1}$] for 2012, the corresponding daily mean
 641 rate [$\text{kg}\cdot\text{day}^{-1}$] and those of GAFSv1.2 and FEERv1.1, and the equivalent daily mean rate
 642 calculated from the GFEDv4.1s monthly values. Note that GFEDv4.1s day-by-day estimates are
 643 also available via scaling of the monthly GFED totals with numbers of active fire detections made
 644 per day across the month (van der Werf *et al.*, 2017). As with monthly totals (Fig. 8), FREM's
 645 daily TPM emission rates (cloud and low-FRP fire adjusted) are very similar to those of FEER,
 646 whilst those of GFED and GFAS are substantially lower - apparently unrealistically so as already
 647 discussed by Kaiser *et al.* (2012), Tosca *et al.* (2013) and Reddington *et al.* (2016). In addition to
 648 the apparently more representative magnitudes, the potential value of the very high temporal
 649 resolution emissions estimates offered by FREM is clear from the fact that hourly rates peak at
 650 more than 500% of the daily means. Fig. 12 provides more detail of this for August 2012,
 651 illustrating the very strong emissions diurnal cycle, and this temporal detail may become
 652 particularly important when linking emissions to atmospheric chemical transport models (e.g. Hyer
 653 *et al.*, 2007; Baldassarre *et al.*, 2015; Roberts *et al.*, 2015).

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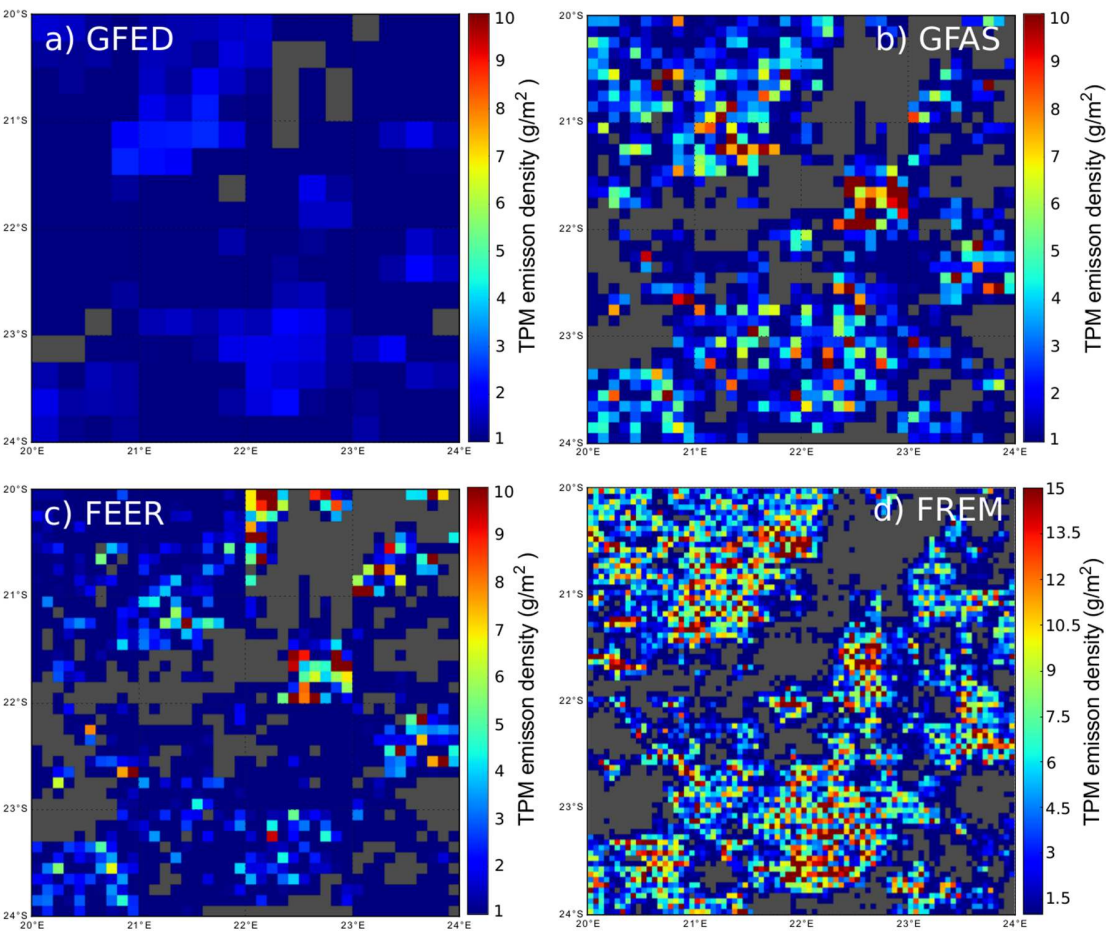
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657 **Figure 11.** Emission rates of total particulate matter (TPM) coming from landscape fires in 2012
 658 across southern Africa, as derived from the FREM methodology applied to SEVIRI FRP-PIXEL
 659 data, and from GFEDv4.1s, GFASv1.2 and FEERv1.1. GFAS and FEER provide daily values, and
 660 GFED monthly values. All are shown as equivalent daily mean rates for comparison, but the
 661 FREM-derived values can be calculated at up to 15-min temporal resolution direct from the
 662 SEVIRI FRP observations. In addition to FREM daily means, FREM-hourly averages are therefore
 663 also shown (rhs y-axis), and these show far higher daytime peaks than the daily averages.



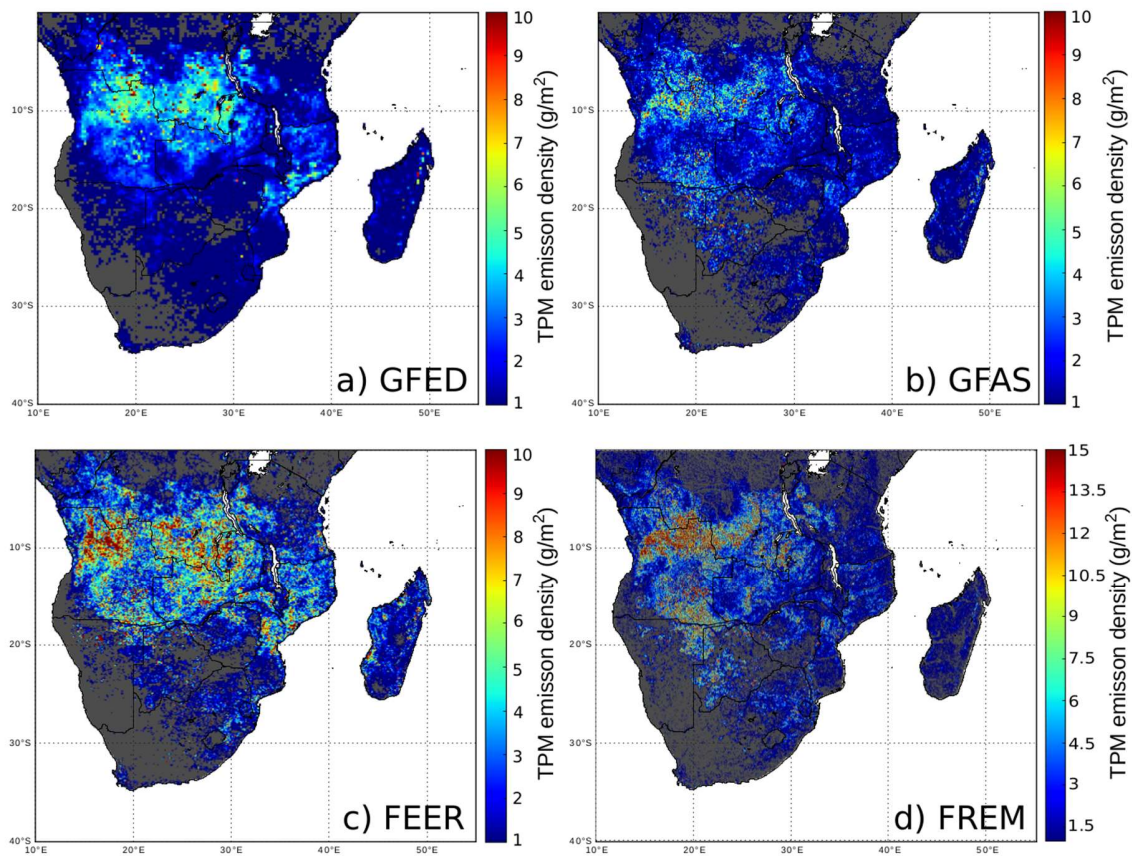
666
 667 **Figure 12.** Data of Fig. 11 shown only for August 2012 to see more detail, particularly of the
 668 strong diurnal variability in TPM emissions enabled by the FREM approach.

670 In addition to its very fine temporal resolution, FREM can operate at the full spatial resolution of
 671 the original FRP observations, which for SEVIRI coarsens to around 0.05° over southern Africa.
 672 The $625\times$, $25\times$ and $25\times$ smaller pixel area than the grid cells of GFED, GFAS and FEER
 673 respectively leads to far finer-grained definition of smoke emission sources (Fig. 13), though the
 674 overall spatial patterns of FREM's emissions sources broadly agrees with the other inventories
 675 (Fig. 14).



676
 677 **Figure 13.** Total particulate matter (TPM) emission density (g.m^{-2} equivalent averaged over each
 678 grid cell) for the $25,000 \text{ km}^2$ area of southern Africa outlined in red in Fig. 3 for 2011, as depicted
 679 by (a) GFEDv4.1s (0.25° grid cells), (b) GFASv1.2 (0.1° grid cells), (c) FEERv1.1 (0.1° grid cells)

680 and (d) FREM inventory (0.05 ° grid cells). The coarser the grid resolution typically the lower the
681 emission density values, since many of the fires typically do not cover entire cells, particularly for
682 the coarser-scale inventories. Results for the FREM cloud and small fire adjusted inventory are
683 shown in (d), with a different colour-bar than for the other inventories. Values for the cloud-
684 adjusted FREM inventory can simply be provided by using the colour bar shown in (a), (b) and (c)
685 also for (d).
686



687
688 **Figure 14.** Total particulate matter (TPM) emission density (g.m^{-2}) across all of southern Africa
689 in 2011, as depicted by (a) GFEDv4.1s (0.25 ° resolution), GFASv1.2 (0.1 ° resolution), FEERv1.1
690 (0.1 ° resolution) and the SEVIRI FRP-derived FREM inventory (0.05 ° resolution). See Fig. 13
691 and its caption for more detail, and note the differing colour bar of (d).

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**6. TRACE GAS & CARBON EMISSIONS, AND
FUEL CONSUMPTION PER UNIT AREA**

6.1 Trace gas Emissions Methodology

Trace gas emissions are estimated in FREM using standard gaseous emissions factors (EF_{GAS}), but applied in a different way to in GFED and GFAS, where they are multiplied by the calculated total fuel consumption (or fuel consumption rate) to estimate total emissions (or emissions rates). Within FREM, trace gas fluxes are instead calculated via direct multiplication of the FRP data by a set of gaseous emissions coefficients, avoiding the intermediate fuel consumption step. These coefficients are calculated via multiplication of the TPM emissions coefficients (Fig. 7; Table 3) and the relevant particulate and trace gas emissions factor ratios (i.e. the ratio of EF_{GAS} to EF_{TPM}), similar to how Huijnen *et al.*, (2016) estimated CO_2 and CH_4 releases from SE Asian fires from optimised estimates of fire-emitted CO. As with the EFs themselves, EF ratios vary markedly by biome, and here we used EF's from Andreae and Merlet (2001) - as do GFED and GFAS - to calculate the gaseous emissions coefficients ($g.MJ^{-1}$) listed in Table 3.

Table 3. Trace gas smoke emission coefficients (and their uncertainties), derived using the ratio of the relevant trace gas emissions factor to total particulate matter emissions factor ($\text{g.kg}^{-1}.\text{g.kg}^{-1}$) and the smoke emissions coefficients (g.MJ^{-1}) for total particulate matter (TPM) shown in Fig. 7 (repeated in the Table). The emissions factors used in the calculation, taken from updates to Andreae and Merlet (2001) presented in Kaiser *et al.* (2012) are also shown. Note the smoke emissions coefficient represents ‘emissions (g) per unit of SEVIRI-observed FRE (MJ)’. Use of geostationary sensors, such as the forthcoming Meteosat Third Generation (MTG), that have a minimum FRP detection limit different than that of SEVIRI (Freeborn *et al.*, 2009; 2014) may result in the need to derive updated coefficients.

	Species Emission Coefficient \pm uncertainty (g.MJ^{-1})				
	Species Emissions Factor (g.kg^{-1})				
	Closed Canopy Forest	Open Canopy Forest/Woodland	Shrubland	Savanna Grassland	Managed Lands
TPM	65.6 ± 0.9 11.8	19.8 ± 0.5 8.5	17.4 ± 1.0 8.5	13.0 ± 0.2 8.5	15.6 ± 0.3 8.5
CO ₂	9044 ± 2506 1626	3825 ± 1460 1646	3361 ± 1296 1646	2523 ± 962 1646	3024 ± 1154 1646
CO	562 ± 189 101	142 ± 71 61	125 ± 64 61	94 ± 47 61	112 ± 56 61
CH ₄	36.7 ± 19.4 6.6	5.1 ± 2.8 2.2	4.5 ± 2.5 2.2	3.4 ± 1.9 2.2	4.0 ± 2.2 2.2

6.2 Trace Gas Emissions Results

725 FREM's CO₂, CO and CH₄ emissions estimates (Fig.14a) show the same seasonal characteristics
726 as those of TPM, with temporal peaks in accordance with GFED. In terms of CO, Pechony *et al.*
727 (2013) report that GFED appears to underestimate emissions in the southern hemisphere, and
728 report the strong influence of the diurnal cycle, with afternoon CO emissions being around double
729 those estimated from the morning overpass of MOPITT. This attests to a potential advantage of
730 the high temporal resolution FREM inventory. Kopacz *et al.* (2010) also report a roughly factor of
731 two difference between GFEDv2 CO emissions for southern Africa and those estimated from
732 adjoint atmospheric inversion of satellite CO observations. Comparison of Van der Werf *et al.*
733 (2010) and <http://www.globalfiredata.org/>) shows a decrease in CO emissions for southern Africa
734 from GFEDv2 to GFEDv4.1s, so the latter appears still to deliver CO emissions lower than satellite
735 CO data may imply. The cloud-adjusted FREM inventory indicates CO emissions 11% and 44%
736 higher on average than GFEDv4.1s and GFASv1.2 respectively, with much larger differences
737 when the low-FRP fire FREM adjustment is included and CO flux magnitudes become very similar
738 to those of FEER (Fig. 14). Similar relationships are seen for CH₄ and CO₂, and the flux of any
739 other trace gases can be easily derived within the FREM framework via the application of the
740 relevant emissions factor ratios.

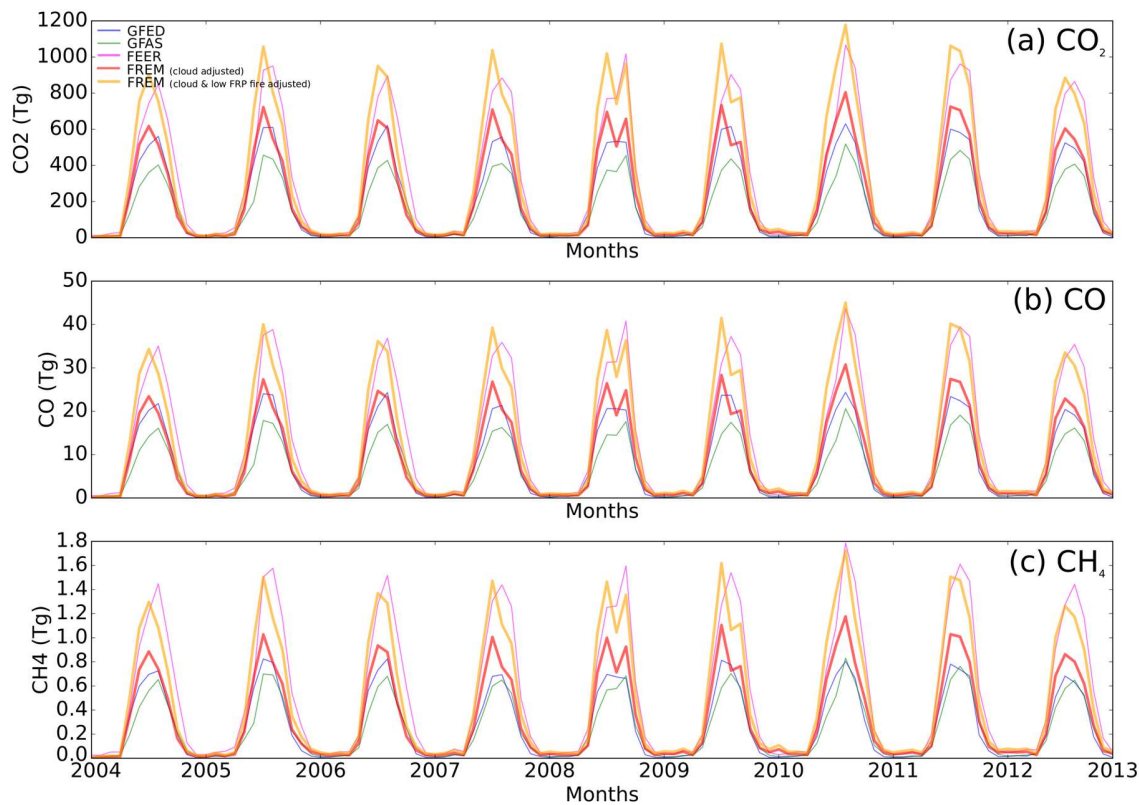


Figure 15. Monthly emissions (Tg) of CO₂, CO and CH₄ for southern Africa (2004-2012) for the FREM inventory, along with those of GFEDv4.1s, GFASv1.2 and FEERv1.1.

6.2 Total Carbon Emissions and Fuel Consumption

Since CO₂, CO and CH₄ are responsible for ~ 99% of carbon emitted by southern African landscape fires (Delmas *et al.*, 1995; Keene *et al.*, 2006), summation of their carbon allows for derivation of total C-emissions. By making the normal assumption that vegetation is $50 \pm 5\%$ carbon, landscape-scale total fuel consumption can then be estimated - for the first time from a fully 'top down' approach. Temporal trends in total C emissions replicate those seen in CO₂ (Fig. 15a), with mean ($\pm 1\sigma$) annual C-emissions of $710 (\pm 61)$ Tg calculated for southern Africa across the nine years of study (range of 213 Tg), rising to $1038 (\pm 88)$ Tg when the low FRP fire adjustment is included. Total fuel consumption is simply calculated as twice the carbon emissions,

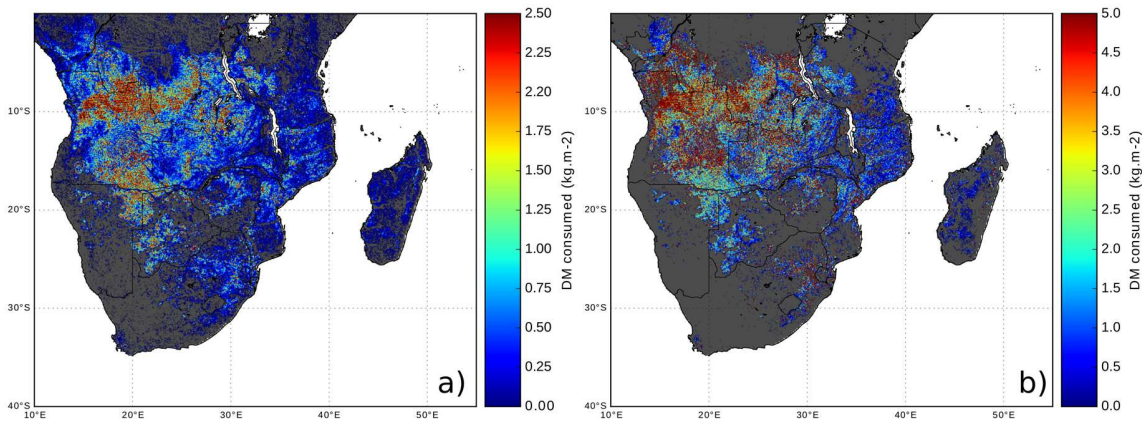
and is 12% higher than GFEDv4.1s and 48% higher than GFASv1.2 based on the cloud-adjusted
 FREM values, and substantially more when the low FRP fire adjustment is included. Fuel
 consumption rates (T_g biomass. sec^{-1}) for a pixel or grid cell can also be directly estimated from
 the TPM emission rates via a simple division by the TPM emissions factors (Table 3), providing
 an estimate of the combustion rate required to produce the inferred TPM fluxes. These fuel
 consumption rates can be temporally integrated to provide a direct estimate of total fuel
 consumption if individual gaseous emissions totals are not required. A related approach can be
 used to derive the equivalent of the FRE-to-dry matter conversion factors (β) of 0.29, 0.78 and
 0.96 kg. MJ^{-1} respectively for agriculture, savannah and tropical forest biomes that Kaiser *et al.*
 (2012) generate via the GFASv1.0 calibration to GFEDv3.1. For low-FRP fire adjusted FREM,
 we find conversion factors of 1.3 kg. MJ^{-1} for managed lands, 1.1 - 1.6 kg. MJ^{-1} for the various
 savannah types, and 3.8 kg. MJ^{-1} for closed canopy forest, each derived via satellite observations
 and TPM EFs alone, rather than calibration against other inventories or independent fuel
 consumption estimates. These conversion factors are substantially higher than the 0.37 kg. MJ^{-1}
 found by Wooster *et al.* (2005) during experiments which measured FRE close to laboratory fires,
 directly because they take into account the factors that affect FRE estimates derived from above
 the canopy and from Earth orbit discussed in Section 2.

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772 6.3 Extension to Fuel Consumption Per Unit Area

A stated advantage of FREM is that it avoids requiring estimates of fuel consumption per unit area
 (F_c ; kg. m^{-2}), which typically come from multiplying fuel load and combustion completeness
 metrics that are generally considered the most uncertain aspects of fire emissions calculations
 (Reid *et al.*, 2009). However, if F_c is needed FREM can be used to estimate it via the inverse of
 the Seiler and Crutzen (1980) emissions methodology employed in GFED, i.e. by dividing the grid

778 cell TPM-derived fuel consumption (Section 6.2) by its burned area. Assuming each fire-affected
 779 0.05° grid cell (i.e. those mapped in Fig. 14d) is completely burned, the mapped F_c values for 2011
 780 are shown in Fig. 16a, with magnitudes appearing broadly reasonable compared to the field
 781 database of Van Leeuwen *et al.* (2014) and model of Hély *et al.* (2003). Higher F_c regions match
 782 closely the locations of greater burning reported in Archibald *et al.* (2009), predominantly in the
 783 southwest of southern Africa. However, numerous of the grid cells are likely to be only partly
 784 burned, so Fig. 16b adjusts for this using the ~ one hundred 500 m spatial resolution MCD64A1
 785 MODIS BA pixels falling in each 0.05° cell. Median F_c values now increase compared to Fig. 16a,
 786 to 2.6 (1.8) kg.m⁻² for Closed Forests, 1.3 (0.9) kg.m⁻² for Shrublands, 1.1 (0.8) kg.m⁻² for Managed
 787 Lands, 1.9 (1.3) kg.m⁻² for Open Forests/Woodland Savannah, and 1.0 (0.7) kg.m⁻² for Grassland
 788 Savannah - with (and without) the FREM low FRP fire adjustment applied. Difficulties in
 789 mapping small burns with 500 m data (Tsela *et al.*, 2014) mean that some grid cells show zero BA,
 790 and so do not report data in Fig. 16b. Closed Forests show a 74% reduction in grid-cell count
 791 compared to Fig. 16a, with the other biomes 18 to 47%. Despite lower numbers of reporting cells
 792 compared to Fig. 16a, significant spatial variability in F_c is still seen in Fig. 16b, and since
 793 MCD64A1 typically underestimates BA (Tsela *et al.*, 2014) F_c values likely tend to
 794 overestimation, whereas those of Fig. 16a likely tend to underestimation. Future enhancements to
 795 the FREM methodology discussed in Section 7, along with use of new 10 to 30 m spatial resolution
 796 BA datasets (e.g. Boschetti *et al.*, 2015) should enable more precise future mapping of F_c via the
 797 approach introduced here.



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Figure 16. (a) Fuel consumption per unit area (F_c) totals, calculated from the TPM emissions (g.m^{-2}) of Fig. 14d divided by the biome-dependent TPM emissions factor (g.kg^{-1}). (b) These data adjusted for the fraction of the grid cell burned, according to the Collection 6 MCD64A1 MODIS burned area product of Giglio *et al.* (2013). Note colour bar differences between (a) and (b), and that whilst (a) contains data for all grid-cells the SEVIRI FRP-PIXEL Product and the FREM inventory denotes as fire-affected, due to some of these cells reporting zero burned area in the MCD64A1 GFED BA area product there are fewer cells where F_c values can be calculated in (b).

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809 7. CONCLUSIONS

810 A new ‘FRE_{emissions}’ (FREM) methodology has been developed to estimate landscape fire
811 emissions of total particulate matter (TPM), trace gases and carbon, based on a combination of
812 geostationary fire radiative energy (FRE) retrievals, polar-orbiting satellite aerosol optical depth
813 (AOD), and particulate and trace gas emissions factors (EFs). ‘Smoke emissions coefficients’
814 (which convert FRP into rate of TPM emissions) are derived from matchup FRE and AOD data of
815 a tiny fraction ($\ll 0.001\%$) of fires present within the dataset, and these are then applied to the full
816 satellite FRP record to derive TPM emissions, and via use of EF ratios to trace gas and carbon as

well. This fully ‘top down’ approach bypasses the fuel consumption step, which is generally considered the most uncertain aspect of fire emissions calculations (Reid *et al.*, 2009; Vermote *et al.*, 2009; van Leeuwen *et al.*, 2014), and thus avoids requiring estimates of fuel load per unit area or combustion completeness. The FREM approach also circumvents use of static, laboratory-derived FRE-to-fuel consumption conversion factors that may not take into account all issues faced when assessing FRE from above the canopy and from Earth orbit (Wooster *et al.*, 2005), whilst also avoiding the need to base such conversion factors on calibrations against bottom-up fuel consumption measures (as is currently done for GFAS; Kaiser *et al.*, 2012), thus providing a totally independent fire emissions estimate to e.g. GFED. If required, fuel consumption per unit area (F_c) measures can be derived a last step to the FREM calculations, based on the inverse of the Seiler and Crutzen (1980) methodology, providing an important new way of mapping this metric across landscapes. Primary uncertainties in FREM pertain to the conversion between AOD and TPM, which relies on the light extinction efficiency per unit of aerosol mass appropriate to biomass burning aerosols (β_e , [$\text{m}^2 \cdot \text{g}^{-1}$]), and the degree to which FRE totals need adjusting for undetected low FRP active fire pixels below the geostationary sensors minimum detection limit. These issues will be the subject of future methodological development. Other anticipated improvements relate to use of finer spatial resolution satellite AOD products, and to greater knowledge of the biome and temporal dependency of particulate matter and trace gas emissions factors, required by FREM as they are for all current fire emissions inventories.

Southern African biomass burning emissions fields from 2004-2012 have been generated via the FREM approach applied to Meteosat SEVIRI FRP data available from the EUMETSAT LSA SAF at a far higher spatio-temporal resolution than existing emissions inventories (hourly; 0.05°). Once adjusted for the low-FRP component of a regions fire regime, the monthly TPM, CO_2 , CO and

841 CH₄ totals are similar to those of the MODIS FRP- and AOD-based FEER inventory (Ichoku and
842 Ellison, 2014), though the geostationary FRP-based FREM methodology avoids assumptions
843 regarding plume height and velocity required when using polar-orbiter FRP ‘snapshots’ (Ichoku
844 and Ellison, 2014). FREM and FEER show significantly higher emissions totals than GFASv1.2
845 and GFEDv4.1s, with the TPM emissions appearing to align better with estimates provided for
846 southern African biomass burning via remotely sensed AOD (e.g. Tosca *et al.*, 2013) and thus
847 which may agree better with atmospheric studies compared to GFED and GFAS. Whilst the
848 representation of smoke aerosol ageing in atmospheric models will play a part in such
849 comparisons, any confirmed GFED underestimation would stem either from additional undetected
850 or low-biased burned areas, too low fuel consumptions per unit area, or inappropriately low
851 emissions factors. Impacts from each will be transferred to GFAS via its calibration to GFED
852 (Kaiser *et al.*, 2012), but only the latter effect would impact FREM (and then only the trace gas
853 estimates, not those of TPM alone). GFEDv4.1s does report a significant increase in carbon
854 emissions from southern African landscape burning compared to GFEDv3, based on the type of
855 ‘small fire boosting’ methodology introduced by Randerson *et al.* (2012), suggesting substantial
856 numbers of MODIS AF pixels are located outside of MODIS-mapped burned areas. We also find
857 many areas where the FRP-based FREM reports emissions, but the 500 m MODIS MCD64A1
858 burned area (BA) product maps zero burning (*c.f.* Fig. 16a and b), but where both provide non-
859 zero data we find calculated fuel consumption per unit area burned (F_c) appear broadly realistic,
860 though with currently large uncertainties at the individual grid-cell level. These will in future be
861 reduced by FREM methodological improvements and higher spatial resolution burned area
862 mapping. Other future work will focus on lessening restrictions on the type of fire available for
863 deriving the smoke emissions coefficients of Fig. 7, as use of the 10 km MODIS AOD product
864 means that large, spatially isolated fires are currently preferred, restricting the number of fires

865 available. The appropriateness of the low-FRP fire adjustment will also be examined, including
866 dependence on view-angle and time of day (Freeborn *et al.*, 2009). The FREM approach will likely
867 benefit from further improvements in the discrimination of fire-relevant biomes, and from
868 enhanced specification of particulate matter emissions factors, something that has generally seen
869 less work than the EFs of trace gases yet which in FREM does impact the trace gas emissions
870 estimates.

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872 FREM provides biomass burning emissions estimates at the highest spatio-temporal scale currently
873 available (i.e. hourly or better, 0.05°), and we believe the technique offers enormous potential to
874 generate datasets suitable for driving detailed plume dispersion modelling that better takes into
875 account fire temporal variability and the strong fire diurnal cycle (e.g. Baldassarre *et al.*, 2015;
876 Roberts *et al.*, 2015). The emissions coefficients necessary to apply the technique to real-time and
877 archived Meteosat SEVIRI FRP-PIXEL data are planned to be made available through the
878 Eumetsat LSA SAF, whilst the fact that Geostationary FRP data are now available from GOES
879 (Xu *et al.*, 2010) and Himawari (Xu *et al.*, 2017) using the same baseline algorithm developed for
880 Meteosat (Wooster *et al.*, 2015; Roberts *et al.*, 2015) means that a consistent, multi-satellite fire
881 emissions dataset for the tropics, sub-tropics and potentially also mid-latitudes is able to be
882 generated using the FREM methodology.

883

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885 MODIS AOD data are distributed freely as part of NASA's MODIS Atmospheric Product Suite
886 (<http://ladsweb.nascom.nasa.gov/>). SEVIRI FRP-PIXEL data were provided by the EUMETSAT
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1250 LIST OF FIGURE CAPTIONS

1251

1252 **Figure 1.** Mapped difference (hrs) between the time of maximum active fire pixel count (i.e. daily
1253 fire activity peak) and the ± 1 hr window encompassing the MODIS local solar overpass time
1254 (which depends on changing location within the MODIS swath). Data are for 2010 and based on
1255 Meteosat Second Generation (MSG) SEVIRI FRP-PIXEL Product available from the
1256 EUMETSAT LSA SAF (Wooster *et al.*, 2015), spatially aggregated into 0.5° grid cells. Subset
1257 graphs show example histograms of FRP-PIXEL active fire detections for three 0.5° grid cells
1258 located over eastern Central African Republic, Northern Mozambique, and southern Kenya, with
1259 a functional fit to these data and the four MODIS overpass windows per day also indicated. Only
1260 fire detections with confidences > 50% are included (Wooster *et al.*, 2015).

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1262 **Figure 2.** Spatial distribution of active fire detection opportunities offered by the MODIS
1263 sampling windows shown in Fig. 1. This is expressed as the ratio of the Meteosat SEVIRI FRP-
1264 PIXEL active fire detections made within the ± 1 hr window surrounding the four daily MODIS
1265 overpass times (shown in Fig. 1) to the total number of daily detections. Source data are those of
1266 Fig. 1.

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Figure 3. FREM biome map of southern Africa, based on reclassification of the GLOBCOVER 2009 landcover map and appearing similar to the woodland/grassland classification of southern Africa derived by Korontzi *et al.* (2004). Outlines show the thirty-one 500 km × 500 km target regions from which matchup fires used to generate the biome-dependent FREM smoke emissions coefficients (C_{biome}) of Fig. 7 were selected. Red outlined region has its FRP time-series shown in Fig. 4.

Figure 4. Time series of SEVIRI hourly active fire pixel detections (grey bins) and hourly FRE (black line) for the 500 km × 500 km region highlighted in red in Fig.3 in August 2011, located south of the Okavango Delta (see imagery in Fig. 5). Overpass times of Terra and Aqua MODIS are shown by green and blue vertical lines respectively, alongside daily solar noon (red) and the daily time of minimum fire activity minimum (magenta). Error bars on hourly FRE are calculated from the FRP uncertainties delivered in the geostationary FRP-PIXEL product (Wooster *et al.*, 2015).

Figure 5. Example region of southern Africa from which matchup fires were selected on the afternoon of 12th Aug 2011, 12:40 UTC (MODIS Aqua overpass). (a) Region outlined in red in Fig. 3, south of the Okavango delta, depicted as a colour composite using data from the Aqua MODIS afternoon overpass [RGB=1(0.6μm), 4(0.55μm), 3(0.47μm)]. Smoke plumes from candidate active fires are outlined with yellow vectors, and the centre locations of each SEVIRI active fire pixel detected from the time of the identified active fire minimum (shown in Fig. 4) up until this Aqua overpass time are shown as red dots. (b) Zoom around the bottom left fire and

1293 plume shown in (a) to indicate detail. The dark burn scar left by the fire can clearly be seen. (c)
1294 Matching MYD04_L2 AOD data derived from the Aqua MODIS overpass shown in (b).

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1297 **Figure 6.** MODIS Aerosol optical depth (AOD) data matching the MODIS image shown in Fig.
1298 5a. The yellow outlines from Fig. 5 here encompass the set of $10\text{ km} \times 10\text{ km}$ MODIS AOD
1299 product pixels that are included in the plume-integrated AOD calculation for each fire. Any pixel
1300 partly or wholly encompassed by the vector is included in the AOD summation, which is then used
1301 to estimate the mass of total particulate matter in the plume. Some areas of apparently high AOD
1302 are unrelated to biomass burning and so are not outlined here, for example that immediately south
1303 of the Okavango Delta (*cf.* Fig. 5) neighbouring a highly reflective salt pan.

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1306 **Figure 7.** Biome dependent smoke emissions coefficients (C_{biome} , g.MJ^{-1}) derived from the slope
1307 of the linear best fit made between the amount of total particulate matter in a plume (grams) and
1308 the amount of radiative energy released by the causal fire (FRE, MJ). Red shaded area represents
1309 the 95% confidence interval on this slope (i.e. the uncertainty in C_{biome}), whilst the grey shaded
1310 area represents the prediction interval (i.e. the interval encompassing to 95% probability the value
1311 of TPM given a single value of FRE). Coefficients are shown for the biomes of (a) Closed Canopy
1312 Forest, (b) Open Canopy Forest and Woodland (Woodland Savanna), (c) Shrublands, (d)
1313 Grasslands (Grassland Savanna), and (e) Managed lands (including Croplands). For each biome,
1314 each data point represents a single fires FRE calculated from a series of Meteosat FRP-PIXEL
1315 products (Fig. 4), and specifically from the fire activity minimum up until the time of the satellite
1316 overpass from which the matching smoke plume TPM was estimated from the MODIS AOD

product (Fig. 5; Fig. 6). Uncertainties in FRE (1σ) are derived from the FRP-PIXEL uncertainty metrics (Wooster *et al.*, 2015), whereas those in TPM are derived from the $\pm 1.0 \text{ m}^2.\text{g}^{-1}$ uncertainty in the assumed smoke aerosol extinction cross-section (Table 1) and the MODIS AOD uncertainty layer. MODIS AOD uncertainties estimates correspond to one-standard-deviation Gaussian confidence interval of the envelopes resulting from the comparison of retrieved AOD data and AERONET measures. These depend on the AOD, QA flag, and viewing geometry (Sayer *et al.*, 2013).

Figure 8. Monthly total particulate emissions estimates for southern African fires, derived from the FRE_{emissions} methodology (FREM) applied to the SEVIRI FRP-PIXEL product of Wooster *et al.* (2015) for 2004-2012. Three versions are shown, those based on ‘raw’ SEVIRI FRP observations, those adjusted for cloud cover, and those adjusted for ‘cloud cover and under-detected low FRP fires’ (see Section 5.1 and 5.2). The associated uncertainties are shown in each case. Corresponding TPM emissions from the GFED v4.1s, GFAS v1.2 and FEER v1.0 inventories are shown for comparison, and the cloud and low FRP fire adjusted FREM values calculated from SEVIRI lie very close to the MODIS-derived FEER estimates.

Figure 9. Percentage of daily FRE calculated from the Meteosat SEVIRI FRP-PIXEL product for 2012 that is released (a) during the ± 1 hr window encompassing the MODIS overpass time, and (b) in each biome. For comparison to the percentage values, fire activity expressed as daily FRE from MSG SEVIRI is also shown (grey line, scaled from 0 to 100%).

1341

1342 **Figure 10.** Cumulative sum of FREM-derived TPM emissions (%), expressed as function of the
1343 per-grid cell FREM-to-GFED v4.1s emissions ratio. Calculations were performed using the 0.25°
1344 grid cells of GFED, and 85% of cells had non-zero values in both inventories. < 1% of cells had a
1345 non-zero Colours are the same as those mapped in Fig. 3. (a) shows the results using the cloud-
1346 corrected FREM, and (b) the cloud and low FRP fire corrected FREM.

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1348

1349 **Figure 11.** Emission rates of total particulate matter (TPM) coming from landscape fires in 2012
1350 across southern Africa, as derived from the FREM methodology applied to SEVIRI FRP-PIXEL
1351 data, and from GFEDv4.1s, GFASv1.2 and FEERv1.1. GFAS and FEER provide daily values, and
1352 GFED monthly values. All are shown as equivalent daily mean rates for comparison, but the
1353 FREM-derived values can be calculated at up to 15-min temporal resolution direct from the
1354 SEVIRI FRP observations. In addition to FREM daily means, FREM-hourly averages are therefore
1355 also shown (rhs y-axis), and these show far higher daytime peaks than the daily averages.

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1358 **Figure 12.** Data of Fig. 11 shown only for August 2012 to see more detail, particularly of the
1359 strong diurnal variability in TPM emissions enabled by the FREM approach.

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1362 **Figure 13.** Total particulate matter (TPM) emission density (g.m^{-2} equivalent averaged over each
1363 grid cell) for the 25,000 km^2 area of southern Africa outlined in red in Fig. 3 for 2011, as depicted
1364 by (a) GFEDv4.1s (0.25° grid cells), (b) GFASv1.2 (0.1° grid cells), (c) FEERv1.1 (0.1° grid cells)

and (d) FREM inventory (0.05 ° grid cells). The coarser the grid resolution typically the lower the emission density values, since many of the fires typically do not cover entire cells, particularly for the coarser-scale inventories. Results for the FREM cloud and small fire adjusted inventory are shown in (d), with a different colour-bar than for the other inventories. Values for the cloud-adjusted FREM inventory can simply be provided by using the colour bar shown in (a), (b) and (c) also for (d).

Figure 14. Total particulate matter (TPM) emission density (g.m^2) across all of southern Africa in 2011, as depicted by (a) GFEDv4.1s (0.25 ° resolution), GFASv1.2 (0.1 ° resolution), FEERv1.1 (0.1 ° resolution) and the SEVIRI FRP-derived FREM inventory (0.05 ° resolution). See Fig. 13 and its caption for more detail, and note the differing colour bar of (d).

Figure 15. Monthly emissions (Tg) of CO_2 , CO and CH_4 for southern Africa (2004-2012) for the FREM inventory, along with those of GFEDv4.1s, GFASv1.2 and FEERv1.1.

Figure 16. (a) Fuel consumption per unit area (F_c) totals, calculated from the TPM emissions (g.m^{-2}) of Fig. 14d divided by the biome-dependent TPM emissions factor (g.kg^{-1}). (b) These data adjusted for the fraction of the grid cell burned, according to the Collection 6 MCD64A1 MODIS burned area product of Giglio *et al.* (2013). Note colour bar differences between (a) and (b), and that whilst (a) contains data for all grid-cells the SEVIRI FRP-PIXEL Product and the FREM inventory denotes as fire-affected, due to some of these cells reporting zero burned area in the MCD64A1 GFED BA area product there are fewer cells where F_c values can be calculated in (b).

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